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A Product's Kansei Appearance Design Method Based on Conditional-Controlled AI Image Generation

Yuanjian Du [1], Xiaoxue Liu [1], Mobing Cai [2] and Kyungjin Park [1,*]

[1] Department of Industrial Design, Hanyang University, ERICA Campus, Ansan 15588, Republic of Korea; popmutu001@hanyang.ac.kr (Y.D.); xiaoxue@hanyang.ac.kr (X.L.)
[2] Department of Engineering Science, University of Oxford, Oxford OX1 3BH, UK; mobing.cai@trinity.ox.ac.uk
* Correspondence: pkj4321@hanyang.ac.kr

Abstract: Accurately grasping users' Kansei needs and rapidly transforming them into product design solutions are key factors in enhancing product competitiveness and sustainability. This paper proposes a product appearance design method based on Kansei engineering and AI image generation technology, integrating other approaches, with household indoor hydroponics as the research subject. First, the web crawler is used to obtain product image samples and user online reviews, and factor analysis (FA) is applied to quickly extract users' Kansei needs. Second, product morphology is used to deconstruct and encode product appearances. Partial least squares regression (PLSR) is then employed to map and quantify the relationships between Kansei needs and design elements, yielding optimal design solutions and one-dimensional sketches. These sketches are subsequently used as controlled conditions in Stable Diffusion (SD), combined with a team-trained Lora model, to generate two-dimensional colored sketches in batches. Finally, evaluations verify that the generated design solutions are satisfactory and meet users' Kansei needs. The results indicate that the proposed product appearance design method not only holds significant implications for the sustainable development of Kansei engineering in product design but also greatly enhances the efficiency of the design process, providing new insights into integrating new technologies and scientific research methods in the field of product design.

Keywords: Kansei engineering; online reviews; AI image generation; factor analysis; product morphology; partial least squares regression; household indoor hydroponics

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1. Introduction

Enhancing product sustainability is key to maintaining corporate competitiveness under continuously evolving consumer demands. It helps companies prevent or reduce product-related risks while differentiating their products from those of competitors [1]. However, in today's market, where new products are constantly emerging, standing out in a highly competitive environment requires companies and designers to meet consumers' personalized needs, thereby achieving product differentiation to enhance sustainability. Studies have shown that the design and development stages of a product determine 80% of its sustainability impact [2]. Therefore, it is crucial to quickly understand consumer needs during these stages, improve design efficiency, and shorten the product development cycle [3]. However, user needs for products are primarily reflected in two aspects: functionality and appearance. With the continuous advancement of product development technologies, achieving differentiation in functional attributes is becoming increasingly difficult [4]. Influenced by experience economy, consumers now prioritize whether products meet their emotional and aesthetic needs when making purchasing decisions [5]. Product appearance is a key factor that influences consumers' emotional needs and aesthetic preferences [6,7]. Moreover, with the growth of online shopping, the importance of product appearance has become even more pronounced [8].

In traditional product design and development stages, the process primarily relies on the designer's personal experience, often regarded as a black-box system [9]. This approach makes it difficult to capture users' mental perceptions, thereby failing to accurately grasp their emotional needs and aesthetic preferences [10]. As product design and development evolve alongside the user-centered design philosophy, understanding users' complex psychological responses has become key to designing products that meet personalized user needs [11,12].

Kansei engineering is a user-centered ergonomic technique used in new product development, primarily aimed at exploring the feelings and perceptions people have when they see a product [13]. It establishes a mapping relationship between users' vague mental perceptions and product image features to identify combinations of product functions that meet users' Kansei needs, thereby providing a solid design basis for generating product concepts [14,15]. In traditional Kansei engineering, the product concept generation stage mainly relies on the designer, who refers to relevant product images along with their professional knowledge and experience to express product concepts in the form of sketches [16,17]. However, generating product concepts is an iterative process that requires continuous modifications. Due to the subjective nature of the designer, it is often challenging to accurately design products that meet users' emotional needs from the outset. If a design does not align with user aesthetics, the designer must refine and improve the concept [18]. Therefore, finding effective methods to shorten the product design cycle not only enhances the sustainability of the product itself but also significantly aids in improving the traditional design processes of Kansei engineering.

Artificial Intelligence (AI) has been widely used across various fields [19], and with the continuous advancement of deep learning technologies, significant progress has been made in the field of image generation [20]. Currently, there are numerous AI image generation techniques, including text-to-image generation, image-to-image generation, sketch-to-image generation, various condition-controlled image generation, scene and panorama generation, and video generation [21], yet, image generation techniques based on Diffusion Models (DM) have garnered particular attention due to their outstanding performance [22]. Although AI image generation technologies based on various methods can already produce images on a large scale, these images can still be regarded as conceptual sketches, while in the field of product design, the quality of a sketch is not determined by the number of images generated but rather by the ability to accurately capture user needs and to design product appearances that meet those needs.

In conclusion, under the context of sustainable development, enhancing product competitiveness and sustainability requires the optimization and improvement of traditional design methods. Although Kansei engineering can explore users' emotional preferences for product appearance, the process of generating product appearance sketches is often lengthy and complex due to various factors, leading to extended design iteration times, low efficiency, and an increased consumption of design resources. While AI image generation technology can produce a large number of images in a short time, whether these images can accurately meet users' needs remains uncertain.

Therefore, the hypothesis of this study is that a product appearance design method based on the theoretical foundation of Kansei engineering, combined with AI image generation technology and scientific methods, and incorporating conditional controls, can efficiently and accurately generate product appearances that align with Kansei needs, thereby optimizing the entire product appearance design process to help enhance sustainable competitiveness. This method also improves the traditional process of generating product appearance sketches in Kansei engineering and offers new ideas on how to integrate new resources and technologies brought by sustainable development into product design through scientific research methods. The research results indicate that the proposed hypothesis, compared to traditional design methods, is innovative in that it introduces new AI image generation technology by integrating a solid theoretical foundation, simplifying the design process, and providing a new perspective for the design and development of sustainable product appearances. This approach reduces the time and resource wastage in the design stage, enhances the rationality and accuracy of the design, and ultimately optimizes the sustainability of the entire product development cycle.

2. Literature Review

2.1. Kansei Engineering

Kansei engineering is a user-centered ergonomic approach that quantifies users' vague perceptions and applies them to new product development [9,14]. Currently, Kansei engineering has been applied in various fields, such as service design [23–26] and architectural and interior design [27–29]. In the development of emotional design for new products, quantitative analysis methods are widely used. For instance, in vehicle design, Chang and Chen analyzed the design elements of car steering wheels using Kansei engineering [14]. Chiu and Lin explored automated bicycle appearance design through text mining and Kansei engineering [30]. Guo and Qu et al. combined Kansei engineering with N400 to study the appearance of SUVs [12]. For in-home appliance design, Kansei engineering has been utilized for designing the appearance of blenders and analyzing the appearance of toasters [31,32]. Additional examples include studies on mobile phones [33,34], train seat designs [35], bamboo pen holders [18], and many other products. A review of the literature suggests that the application of Kansei engineering in product design can be divided into three main stages: extracting user perceptions for emotional modeling, identifying product design elements and establishing mapping relationships with user perceptions, and generating product concept sketches to guide the final design process.

However, most studies conclude with the prioritization of product design elements or the presentation of one-dimensional sketches. Although these findings can guide the final design of subsequent products, they still contain considerable uncertainties. The theoretical results or sketch-like drawings do not visually present a complete concept of the product, leaving room for interpretation and the potential influence of subjective factors in the formation of the final product concept. Research by Liu and Yang has also demonstrated that 3D images, which more closely resemble real products, allow people to understand the product more easily and accurately while also providing a more intuitive display of the product's actual appearance [36].

2.2. Product Morphological Analysis

Morphological analysis is used in product design to study product forms [37,38]. To accurately identify the correspondence between various design elements of a product and user perceptions, it is necessary to deconstruct the key design elements of the product and establish a mapping model with users' emotional data. Product morphological analysis views the product as an integrated system and deconstructs it into individual elements according to different projects or categories, coding these elements. By predicting the relationship between these elements and user perceptions properly, this approach identifies key design elements and develops innovative and rational design solutions. Since this method can simply and intuitively present the morphological characteristics of products, it is also widely used in Kansei engineering [39]. Examples include women's coat design based on product morphological analysis [40], coffee maker appearance design [38,41], research on disposable razor appearance [42], bicycle appearance design and evaluation [43], and soccer shoe design [15].

Therefore, through a rational analysis of the overall product morphology combined with Kansei engineering, it is possible to effectively and accurately predict the design elements that users desire in the final appearance of the product. It is essential to fully and realistically express the design proposals composed of these elements, as this plays a crucial role in the subsequent evaluation of the design proposals and in transforming these proposals into the final product.

2.3. AI Image Generation

In recent years, AI-based deep learning image generation technology has become a popular research area. Due to its ability to generate realistic images and its efficient image generation capabilities, it has also been widely explored and applied in the field of product design. Recently, Convolutional Neural Networks (CNN) [44] and Generative Adversarial Networks (GAN) [45], which generate images through adversarial learning, have started to be used in product design. For example, Pedro et al. utilized CNNs to evaluate the availability of thermostats [46]; Zhou et al. applied CNNs to classify front face images of cars to train adversarial neural networks [47]; Pan et al. developed a model using deep learning to predict customers' aesthetic attributes [48]; Chai et al. studied automatic sketch coloring models based on GANs [49]; Li et al. combined Kansei engineering with GANs to generate numerous product concept sketches [10]; Wang et al. integrated Midjourney with other mathematical models to discuss the appearance of women's electric vehicles [50]; and Wu et al. used vacuum cleaners as an example to discuss the practical application of artificial intelligence-generated content (AIGC) in product color schemes [51]. Although these methods enhance the innovative capacity of design, their training processes are highly complex, affecting image generation efficiency and limiting their accessibility to users. The emergence of Diffusion Models (DM) [52] has garnered broader attention due to their outstanding stability and greater extensibility [53]. A series of studies have shown that DMs outperform GANs in terms of image clarity, realism, and diversity [54,55]. In this paper, Stable Diffusion (SD) [56], an improved version of DM, is adopted, introducing latent vector spaces to efficiently generate high-resolution images. The principle of text-to-image generation used in this method is illustrated in Figure 1.

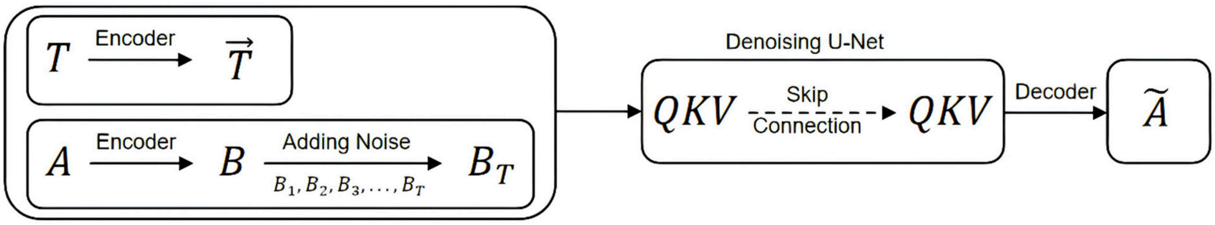


Figure 1. The Principle of Text-to-Image Generation.

In the figure, T represents the input text prompt. After being encoded by the encoder, the text is transformed into a Text Embedding, denoted as $\vec{T}$, which is used to guide the image generation. A represents the original image, which, after being encoded by the encoder, is converted into a latent representation B. The process from B to B_T is the Diffusion Process, a step-by-step addition of noise to the image in the latent space, where B_1, B_2, and B_3 represent latent representations at different time steps until a near-pure noise representation B_T is obtained. The next step is the denoising process for the image, where a U-Net structured model is applied. The U-Net employs a Cross-Attention mechanism, which is depicted in the figure as text-guided image generation, i.e., QKV, where Q is the query vector, typically derived from the current intermediate feature representation; and K and V are the key and value, usually derived from the conditional input, representing the text embeddings in this diagram. Cross-attention can also be expressed as Attention QKV, as shown in Equation (1).

$$\text{Attention } QKV = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V, \;\; Q = W_Q \cdot \varnothing i(z_t), \;\; K = W_K \cdot T\varnothing(y), \;\; V = W_V \cdot T\varnothing(y) \tag{1}$$

In this context, $\varnothing i(z_t)$ represents the intermediate representation of the U-Net, and $T\varnothing(y)$ in the diagram refers to the text embedding. W_Q, W_K, and W_V are learnable projection matrices. This can be understood as calculating the dot product between the query and key vectors, applying the softmax function to obtain attention weights, and then applying these weights to the value vectors. This mechanism allows the model to effectively refer to and integrate information from the conditional input during image generation.

Finally, the final image $\widetilde{A}$ is obtained through the decoder.

ControlNet

Although Stable Diffusion (SD) can generate high-quality images from text input, controlling the spatial composition of images solely through text is highly complex and limited. Consequently, researchers have started exploring various methods for adding additional control modes to SD to achieve the desired outcomes [22]. ControlNet, a neural network architecture, allows for the addition of spatial condition control to SD [57]. Its basic principle is to retain the quality and functionality of large models while locking their parameters and creating trainable copies of the encoding layers, which are connected via zero convolution layers, as illustrated in Figure 2.

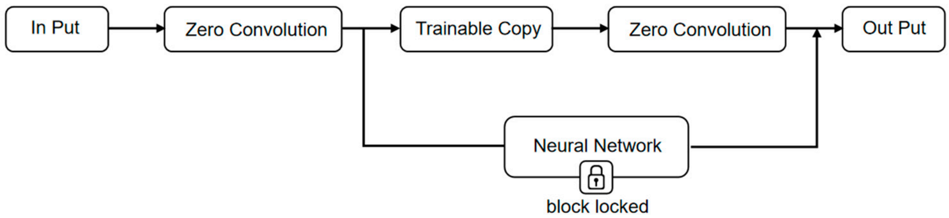


Figure 2. Basic Principle of ControlNet.

Currently, ControlNet can colorize black-and-white sketches or convert them into realistic product images in various ways, with impressive results. This capability can greatly facilitate the rapid transformation of product sketch solutions obtained through methods such as Kansei engineering into actual images, helping designers and users quickly understand the product.

In conclusion, Kansei engineering can be used to explore users' emotional needs and, combined with product morphological analysis, construct a mapping model between emotional data and product appearance design elements. The optimal design solution obtained can be used as a control condition in the AI image generation process to ensure that the final product appearance images generated are both reasonable and desirable.

3. Materials and Methods

After selecting a suitable product as the research subject, the study first collected product images and reviews by web scraping. A combination of qualitative and quantitative methods was used to filter the data, such as categorizing and eliminating images through expert panels, and the KJ method was used to obtain the required image samples. Factor Analysis (FA) was then used to determine the Kansei word groups needed for the study. Subsequently, a qualitative research method—product morphological deconstruction—was employed to deconstruct the design elements of the product appearance. The quantitative method Partial Least Squares Regression (PLSR) was then used to construct the mapping relationship between the deconstructed elements and the Kansei word groups, resulting in a one-dimensional black-and-white design sketch of the product. Finally, an appropriate AI image generation platform was selected, and different conditional controls were applied to generate the final product concept sketches. The reasonableness of the proposed hypothetical design method was verified through a simple evaluation of the generated sketches. The following section provides a detailed description of the methods used in this study.

3.1. Extracting Kansei Data

The objective of this stage is to obtain users' Kansei data related to the research product using rational and efficient methods. In traditional Kansei engineering, the phase of extracting user Kansei data primarily relied on literature reviews, focus interviews, and group discussions. However, these methods faced numerous limitations, such as being time-consuming, being highly subjective, and having small sample sizes [58,59]. With the development of the internet, an increasing number of researchers have been identifying users' emotional needs through web text mining and analysis [4,60,61]. Therefore, this study primarily used shopping websites, supplemented by other sources where relevant information on the product could be obtained. By crawling the internet for images, related descriptions, and reviews of the product, preliminary Kansei data on users' perceptions of the product were collected. After the initial stage of Kansei word extraction and image collection, these texts and images were further filtered and processed.

3.1.1. Image Processing

To obtain representative product images, it is necessary to preprocess the extracted product images.

Step 1: If the number of obtained images is too large, the images need to be categorized and filtered first, retaining only the most representative product images.

Step 2: The image formats need to be standardized. In this study, all images were processed uniformly into JPG format with a resolution of 512 × 512 pixels. To prevent other elements besides the product itself from introducing unnecessary subjective influences in subsequent experiments or tests, Photoshop was used at this stage to retain only the product in the images while removing other irrelevant elements, such as cluttered backgrounds, brand logos, and brand information.

Step 3: Finally, a panel of experts conducts a group discussion to filter and select the final set of images.

3.1.2. Selection of Kansei Words

The purpose of this stage is to determine the Kansei words needed for this study.

Step1: After completing the text mining of customer reviews and product descriptions from the internet, the texts need to be filtered to preliminarily identify suitable Kansei words for describing the product. Studies by Yang and Liu, Liu, and Du all indicated that adjectives are more suitable for Kansei words in describing products [5,36,62]. Therefore, the preliminary texts need to be processed to select words that are suitable for describing the product, especially adjectives.

Step 2: If the number of retained words is still too large, further filtering is required, mainly to eliminate adjectives that do not apply to the product appearance and words that lack practical significance. The KJ method is useful for sorting data from the bottom up [63]. Therefore, at this stage, the KJ method combined with focus group discussions will be used for further screening.

Step 3: Further dimensionality reduction is applied to synonymous or similar words to obtain the final set of Kansei words. At this stage, most researchers have used Factor Analysis (FA) to reduce the dimensionality of these words. As a multivariate statistical method, Factor Analysis can reduce variables and extract the main elements [41]. For example, Woo et al. used Factor Analysis to reduce the dimensionality of Kansei words obtained from online reviews of electric toothbrushes [60]. Similarly, Jin et al. employed Factor Analysis to reduce the dimensionality of Kansei words in online reviews [64]. The process for obtaining the final Kansei words through Factor Analysis is as follows:

1. Design a reasonable questionnaire. This study used an online questionnaire. First, representative product images were selected as a medium for participants to understand the product's appearance. Next, the Kansei words obtained from the previous step were used as questions in a 5-point Likert scale format, where participants rated the suitability of each adjective in describing the product's appearance.
2. Conduct Factor Analysis on the questionnaire results. The questionnaire results are entered into SPSS V26.0.0 for analysis. After verifying the validity and reliability of the questionnaire results and other test outcomes, all words are classified, and the classified factors are named to obtain the final set of Kansei words.

3.2. Product Deconstruction and Construction of the Mapping Relationship

The purpose of this stage is to obtain the sketch of the optimal design solution. At this stage, it is necessary to link the semantic space (i.e., the selected Kansei words) with the property space (i.e., the design elements included in the product appearance) to establish the relationship between them.

Step 1: To determine the property space, which includes the design elements of the product appearance, a detailed deconstruction of the overall appearance of the product being studied is required using product morphological analysis. The product appearance is deconstructed based on three key factors: form, color, and material. The deconstruction of form will be presented in the form of black-and-white wireframe drawings.

Step 2: The deconstructed elements are named and encoded to facilitate the subsequent construction of the mapping relationship between the semantic space and the property space. There are many methods for constructing mapping relationships, such as Quality Function Deployment (QFD) [65], Linear Regression and Multiple Linear Regression [66], Quantification Theory Type I (QTI) [67], Support Vector Regression (SVR) [68], and many other effective scientific approaches. This study employed Partial Least Squares Regression (PLSR) [69] to investigate the mapping relationship between Kansei words and the design elements in the product appearance. The main reasons for choosing this method were as follows: First, unlike ordinary least squares regression (OLS), Partial Least Squares Regression (PLSR) is typically used to address datasets with complex structures, multicollinearity issues, and difficulties in making prior assumptions. It is suitable for constructing predictive models and can predict multiple variables using a relatively small sample size without requiring prior assumptions about the correlation between variables. Second, this method had also been proven to be effective in Kansei engineering studies for building the mapping relationship between semantic space and property space [41,70,71]. Therefore, using PLSR to construct the mapping relationship between Kansei words and design elements was highly suitable for this study. In this process, the deconstructed design elements of the product appearance were combined with the final set of Kansei words, and the results were statistically analyzed through an online questionnaire. A 5-point Likert scale was used, and the participants were asked about the correlation between the design elements and the Kansei words.

Step 3: Collect the questionnaire results and conduct PLSR analysis using Microsoft Excel XLSTAT 2021 to identify the design elements in the product appearance attributes that have the highest correlation with the Kansei words. Finally, these design elements are integrated to construct the optimal design solution sketch, which is presented as a one-dimensional black-and-white sketch.

3.3. AI Image Generation Method

The purpose of this stage is to use AI image generation technology to produce the final product concept images based on the research process. The AI image generation part of this study explores the hypothetical design solutions for indoor hydroponic products based on Stable Diffusion (SD). Stable Diffusion is a powerful image generation tool that can run locally for free, and multiple online services currently allow users to utilize different versions of SD, such as DreamStudio (https://dreamstudio.ai/), Stable Diffusion Online (https://stablediffusionweb.com/), Hugging Face (Stable Diffusion 2-1—a Hugging Face Space by stabilityai), and Stable Diffusion WebUI (GitHub—AUTOMATIC1111/stable-diffusion-webui) [72]. In this study, the Stable Diffusion WebUI interface was used to generate the images needed for the research.

Step 1: First, test the generation of product appearance images by SD using only input prompts. Considering that the Stable Diffusion WebUI alone may not accurately generate the product appearance studied in this paper, it may be necessary to add additional conditions to SD to align it with the desired product appearance of this study.

Step 2: At this stage, an LoRA model [73] suitable for SD will be trained to assist SD in generating the product appearance images required for this study. As a fine-tuning model, LoRA can be combined with the checkpoint to influence the generated results, significantly saving training time and resources while enhancing the accuracy of subsequent outputs [74]. The process of training an LoRA model first requires preparing an image training set. After completing the preparation of the training set, the training can be completed by using an appropriate training framework and continuously adjusting the parameters.

Step 3: Apply conditional control during the image generation process using ControlNet suitable for SD to generate the final product appearance images. This stage aims to ensure that the generated product images have a similar appearance to the black-and-white sketches obtained through the PLSR predictive model.

In summary, the research was divided into five stages. In the first stage, to effectively combine these two approaches, a suitable product needs to be selected as the research subject. Considering the current trend of green, sustainable, and intelligent products, we selected household indoor hydroponic products as the research subject and provided a brief description of them. The second stage involved data collection and filtering for the selected products, primarily including the collection and screening of product image samples and related Kansei words. In the third stage, product morphological analysis was used to deconstruct the product and map it with the previously selected Kansei words, resulting in the optimal design solution for the product's appearance. In the fourth stage, an LoRA model trained for Stable Diffusion (SD) was used as a prompt to help grasp the general appearance of the product, and the optimal design solution from the previous stage was used as a control condition for SD to generate the final product concept sketches. The fifth and final stage involved evaluating the generated product concept sketches. The overall research process is illustrated in Figure 3.

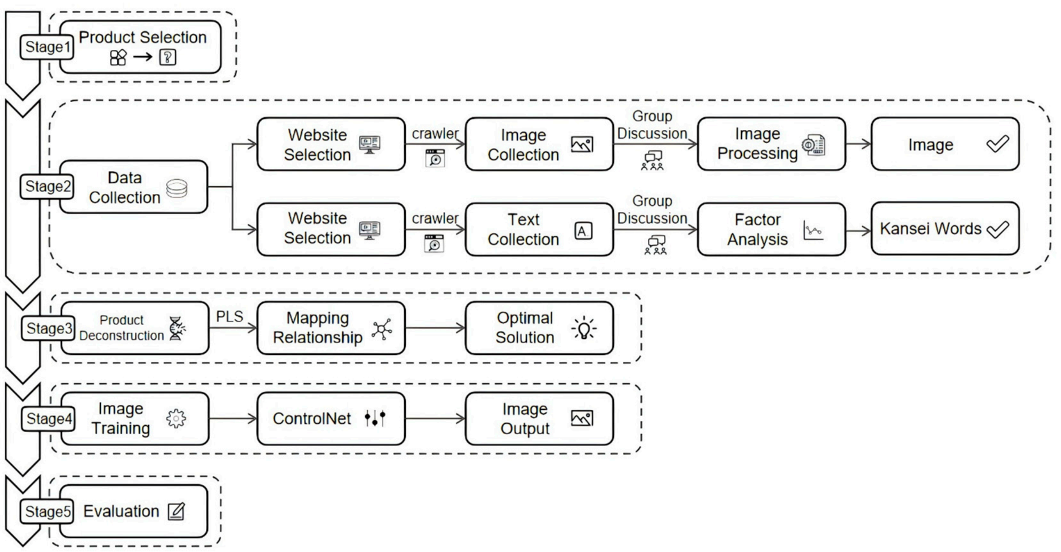


Figure 3. Research Process.

4. Processes and Results

4.1. Selection of Research Objects

This study focuses on household indoor hydroponic devices as the research subject due to several important characteristics of this product. First, hydroponic cultivation is an environmentally friendly technology that not only increases the yield but also does not require large areas of land [75]. Second, as an effective means of food production, hydroponics is less affected by environmental conditions and can be used in regions with limited water resources, severe land pollution, or declining soil fertility [76,77]. Lastly, in the context of increasing urbanization, people living in urban areas can also use this method to cultivate vegetables and plants indoors. As a green, sustainable, and intelligent product that is both environmentally friendly and beneficial to people's lives, there is still a significant gap in research on the appearance of this product [75]. Therefore, studying the appearance of indoor hydroponic devices not only helps validate the rationality of the proposed design process but also fills the gap in the appearance design field of this emerging product. It contributes to the comprehensive development of the product in the future and has a positive impact on promoting green and sustainable development.

4.2. Extraction of Kansei Words and Images

This study initially selected two Chinese shopping websites, 'Taobao' (https://www.taobao.com, accessed on 1 June 2024) and 'Jing Dong' (https://www.jd.com, accessed on 1 June 2024), as well as the overseas shopping platform 'Amazon' (https://www.amazon.com, accessed on 2 June 2024), using 'indoor hydroponics' as the search keyword to perform text mining of product-related reviews and image collection. As an emerging product in recent years, the variety of products was found to be limited, with many duplicates during image sampling. Therefore, we filtered the data by sales volume, selecting reviews and corresponding images for a total of 116 products from the first page of each shopping website. Additionally, considering that indoor hydroponics is a new product with significant growth potential in the future, we expanded our text mining and image collection to include design websites with the same products. The collected texts mainly included product descriptions and evaluations of design works. The selected design websites were 'Puxiang' (https://www.puxiang.com/, accessed on 4 June 2024) and 'Behance' (https://www.behance.net/, accessed on 4 June 2024). Products on these websites are created by professional designers or design teams, resulting in more professional product descriptions and clearer displayed images.

4.2.1. Processing Images

After conducting product image mining on various websites, duplicate products were removed, resulting in a preliminary set of 248 images from 62 products captured from different angles, all in JPG format. Photoshop was used to process the image backgrounds, setting a white background and removing other elements irrelevant to the main product. Brand logos were uniformly removed, and brand information was blurred. Finally, the image dimensions were standardized to 512 $\times$ 512 pixels, ensuring that the image samples were clearly visible while also enhancing the efficiency of subsequent AI image training.

To further understand the design elements in product appearances, a focus group of 10 product design experts was formed to categorize the visual forms shown in the image samples. The group consisted of two professors, four doctoral students, and four graduate students, all specializing in product design. After removing overly conceptual product images (which often came from design websites and included excessive subjective input from designers without sufficient market research) and products with nearly identical appearances, 54 products were retained, as shown in Figure 4.

4.2.2. Obtain Kansei Words

After completing the text mining of customer reviews and product descriptions from the internet, the texts were filtered to preliminarily identify suitable Kansei words for describing the products. Therefore, we processed the mined texts by removing duplicates, performing word segmentation, and classifying the words by part of speech, resulting in a total of 128 adjectives. After further excluding adjectives that were not applicable to product appearance, we preliminarily obtained 77 adjectives related to product appearance, as shown in Table 1.

Figure 4. Product Images.

Table 1. 77 Adjectives Related to Product Appearance.

77 Adjectives						
Simple	Satisfactory	Lightweight	High-end	Personalized	Harmonious	Complex
Accurate	Comfortable	Bulky	Sturdy	Smooth	Enjoyable	Boring
Fast	Surprising	Futuristic	Attractive	Professional	Textured	Popular
Reliable	Average	Technological	Aesthetic	Low-key	Rounded	Dangerous
Safe	Suitable	Traditional	Bright	Quiet	Warm	Fragile
Pleasant	Outstanding	Unsafe	Unique	Delicate	Lively	Rough
Appropriate	Clean	Practical	Plain	Portable	Elegant	Inexpensive
Small	Helpful	Durable	Modern	Minimalist	Premium	Fragile
Ordinary	Convenient	Complicated	Relaxing	Environmentally friendly	Sustainable	Unattractive
Luxurious	Cold	Monotonous	Casual	Difficult to understand	Geometric	Friendly
Impractical	Unpretentious	Cute	Interesting	Modest	Young	Restrained

Since the number of words is still quite large, some of them, such as 'accurate', 'unattractive', 'practical', 'fast', and others, do not have practical significance for studying product appearance, and there are also synonymous or similar words like 'appropriately sized' and 'compact,' it is necessary to further filter and reduce these words to design an optimal product appearance that meets users' emotional needs. Additionally, any negative words should be removed. For further screening and dimensionality reduction, this study first uses the Affinity Diagram (KJ method) to cluster these words. In this stage, we employed a 10-person focus group comprising the same design professionals from the previous image processing stage. The group first removed words that lacked practical significance. To accurately identify the favorable Kansei factors in product appearance, they also removed words with negative connotations. After the first round of elimination and filtering, 42 suitable adjectives were retained, as shown in Table 2.

Table 2. 42 Adjectives Suitable for Describing Product Appearance.

42 Adjectives Suitable for Describing Product Appearance						
Pleasant	Satisfactory	Comfortable	Friendly	Outstanding	Interesting	Unique
Attractive	Personalized	Geometric	Surprising	Appropriate	Luxurious	High-end
Premium	Harmonious	Sustainable	Smooth	Rounded	Elegant	Delicate
Textured	Cute	Relaxing	Generous	Minimalist	Clean	Bright
Safe	Lively	Aesthetic	Modern	Reliable	Warm	Sturdy
Professional	Environmentally friendly	Futuristic	Technological	Unpretentious	Enjoyable	Simple

Next, Factor Analysis (FA) was used to further reduce the dimensions of synonymous or similar words to obtain the final set of Kansei words.

This study designed an online survey questionnaire for the screening of Kansei words. To help participants intuitively understand the product's appearance, six representative images were selected as typical samples for testing through discussion. The selection criteria were based on the inclusiveness of product appearance; it was determined that the shapes, colors, and materials of these six product images encompass the appearance characteristics of all 54 products. Consequently, the six representative product image samples shown in Figure 5 were selected. To ensure fairness, the influence of different plants was removed from all products, and each image was set to a size of 512 × 512 pixels and a white background.

Figure 5. 6 Representative Product Images with Distinctive Appearances.

Based on the first round of screening, the 42 adjectives were incorporated into a questionnaire using a 5-point Likert scale. The participants were asked to rate the suitability of each adjective in describing the appearance of the products shown in the images: 1 represented 'not suitable', 2 represented 'somewhat unsuitable', 3 represented 'neutral', 4 represented 'somewhat suitable', and 5 represented 'suitable'. To ensure the results were as reasonable and professional as possible, all participants were students or professionals related to design. A total of 107 questionnaires were distributed, with 97 valid responses collected. The results were analyzed using SPSS V26.0.0, and the findings are as follows. The Cronbach's alpha coefficient of the questionnaire was 0.989, indicating the high reliability of the data. The KMO value for the questionnaire was 0.959, demonstrating that it was highly suitable for Factor Analysis. Bartlett's test of sphericity yielded a significance of 0.000, indicating that the data were independent and spherically distributed and also making it appropriate for Factor Analysis. These results confirm that the Factor Analysis conducted for the further dimensionality reduction of the Kansei words was accurate and reasonable.

During the Factor Analysis of the questionnaire results, it was found that when the number of factors extracted was set to eight, the total variance explanation rate reached 80.467%. Therefore, clustering the Kansei words based on eight factors was considered the most reasonable approach. The factors were rotated using the Maximum Variance Method and arranged in descending order based on their values. The Kansei words with the highest communalities within each factor were retained, resulting in the final set of Kansei words associated with each factor, as shown in Table 3.

Table 3. Kansei Words Included in Each of the Eight Factors and Their Corresponding Values.

Words	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Comfortable	0.728							
Appropriate	0.596							
Relaxing	0.561							
Satisfactory	0.530							
Enjoyable	0.524							
Lively	0.522							
Warm	0.511							
Friendly	0.477							
Pleasant	0.451							
Outstanding	0.418							
Smooth		0.698						
Rounded		0.548						
Elegant		0.499						
Minimalist		0.496						
Delicate		0.475						
Harmonious		0.456						
Aesthetic		0.452						
Generous		0.439						
Sustainable			0.701					
Environmentally friendly			0.539					
Attractive				0.687				
Cute				0.573				
Interesting				0.412				
Professional					0.679			
Sturdy					0.573			
Safe					0.553			
Reliable					0.538			
Textured					0.397			
Personalized						0.634		
Geometric						0.554		

Table 3. *Cont.*

Words	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Modern						0.538		
Futuristic						0.527		
Unique						0.475		
Technological						0.471		
Clean							0.559	
Unpretentious							0.547	
Simple							0.504	
Bright							0.477	
High-end								0.574
Luxurious								0.542
Surprising								0.480
Premium								0.431

To facilitate the subsequent research, it is necessary to assign names to the factors. Based on the meanings of the Kansei words contained within each factor and the highest-scoring Kansei words, the factors were summarized as follows: Factor 1 mainly focused on the sense of satisfaction and comfort that the product brings to users and was therefore named 'Comfortable and Pleasant'. Factor 2 emphasized the aesthetics, elegance, and smoothness of the overall product design; hence, it was named 'Aesthetic and Harmonic'. Factor 3 included only the terms 'Sustainable' and 'Environmentally Friendly' and was thus named 'Green and Eco-Friendly'. Factor 4 highlighted the product's attractiveness, so it was called 'Attractive'. Factor 5 focused on the safety attributes of the product; hence, it was named 'Safe and Reliable'. Factor 6 centered on the unique feelings brought by the product's style and was therefore called 'Individual and Unique'. Factor 7 emphasized the simplicity and freshness of the product; thus, it was named 'Simple and Clean'. Factor 8 highlighted the sense of luxury associated with the product; hence, it was named 'High-End and Luxury'. Through the above screening and analysis, eight suitable Kansei word groups were ultimately determined, as shown in Table 4.

Table 4. The Final Eight Determined Kansei Word Groups.

Comfortable and Pleasant	Aesthetic and Harmonic	Green and Eco-Friendly	Attractive
Safe and Reliable	Individual and Unique	Simple and Clean	High-End and Luxury

4.3. Product Morphology Deconstruction

Following the three key factors of product appearance—form, color, and material—and based on the analysis and discussion of the selected 54 images, the main views were divided into the front view, right view, and top view and simplified into wireframe forms to facilitate the output of subsequent design sketches. It is important to note that, during the wireframe drawing of product shapes, some shapes were too similar and were therefore grouped into the same category, resulting in 21 representative product samples. Subsequently, the colors and materials of these products were deconstructed and categorized. The produced deconstructed elements were then classified, named, and encoded. To facilitate the construction of the mapping relationship between the semantic space and the property space, the encoding was carried out in binary format: 0 indicates that the product does not have the attribute, while 1 indicates that it does. Detailed deconstruction results and encoding are provided in Appendices A and B.

4.3.1. Constructing the Mapping Relationship

We designed and distributed a questionnaire based on the eight Kansei word groups obtained from the Factor Analysis and the design elements deconstructed from the product morphology, as detailed in Appendices A and B. The main focus of the questionnaire was to investigate the participants' perceptions of the relationship between product elements and Kansei word groups. The survey employed a 5-point Likert scale, where 1 indicated that the element did not evoke the emotions of the corresponding Kansei word group, 2 meant it rarely did, 3 was neutral, 4 indicated it somewhat did, and 5 indicated that the element evoked the emotions of the corresponding Kansei word group. In the questionnaire regarding the relationship between wireframes and Kansei words, we excluded the 'Green and Eco-Friendly' term after discussion, as it is challenging to elicit perceptions related to this term using black-and-white sketches alone. To ensure the professionalism and accuracy of the questionnaire, we invited 120 participants related to the field of product design, including professionals, undergraduates, and graduate students. The questionnaire content was strictly confined to the experimental topic and did not include personal information about the participants. After collecting the responses, we excluded questionnaires that were completed too quickly or had incomplete answers, resulting in 116 valid responses. We then organized the questionnaire data and calculated the average scores for the elements corresponding to the Kansei word groups. Using Microsoft Excel XLSTAT, we conducted a Partial Least Squares Regression analysis combining the virtual variables of the corresponding elements, obtaining regression relationships between the Kansei words and the elements included in product form, color, and material.

All the Kansei word group values in the tables were standardized. When the regression coefficient in the tables is negative, a larger absolute value indicates a weaker relationship between the element and the corresponding word group. Conversely, when the regression coefficient is positive, a larger absolute value indicates a stronger correlation. The highest positive values are highlighted in bold in the tables. The detailed results are presented in Tables 5–7.

Table 5. Regression Relationships Between Kansei Word Groups and Form Elements Across Three Views. The highest positive values in the table are shown in bold.

Regression Coefficients between Kansei Word Groups and Form Elements in the Front View							
	Comfortable and Pleasant	**Aesthetic and Harmonic**	**Attractive**	**Safe and Reliable**	**Individual and Unique**	**Simple and Clean**	**High-End and Luxury**
A1	−0.061	−0.06	−0.065	−0.053	−0.055	−0.033	−0.059
A2	0.007	0.007	0.008	0.006	0.006	0.004	0.007
A3	0.108	0.106	0.116	0.094	0.097	0.058	0.105
A4	−0.029	−0.028	−0.031	−0.025	−0.026	−0.015	−0.028
A5	−0.272	−0.268	−0.292	−0.238	−0.244	−0.146	−0.264
A6	−0.202	−0.199	−0.217	−0.177	−0.181	−0.109	−0.196
A7	−0.387	−0.381	−0.416	−0.339	−0.347	−0.208	−0.376
A8	−0.297	−0.293	−0.319	−0.26	−0.267	−0.16	−0.289
A9	0.175	0.172	0.188	0.153	0.157	0.094	0.17
A10	−0.074	−0.073	−0.08	−0.065	−0.067	−0.04	−0.072
A11	−0.054	−0.054	−0.058	−0.048	−0.049	−0.029	−0.053
A12	−0.055	−0.054	−0.059	−0.048	−0.05	−0.03	−0.054
A13	**0.341**	**0.336**	**0.367**	**0.299**	**0.306**	**0.183**	**0.332**
A14	−0.18	−0.178	−0.194	−0.158	−0.162	−0.097	−0.175

Table 5. *Cont.*

Regression Coefficients between Kansei Word Groups and Form Elements in the Front View							
	Comfortable and Pleasant	Aesthetic and Harmonic	Attractive	Safe and Reliable	Individual and Unique	Simple and Clean	High-End and Luxury
A15	0.15	0.148	0.161	0.131	0.135	0.081	0.146
A16	0.073	0.072	0.078	0.064	0.065	0.039	0.071
A17	0.204	0.201	0.22	0.179	0.183	0.11	0.199
A18	0.207	0.204	0.222	0.181	0.186	0.111	0.201
A19	0.155	0.152	0.166	0.135	0.139	0.083	0.15
A20	0.208	0.205	0.223	0.182	0.186	0.112	0.202
A21	−0.016	−0.016	−0.017	−0.014	−0.014	−0.009	−0.016
Regression Coefficients between Kansei Word Groups and Form Elements in the Right View							
	Comfortable and Pleasant	Aesthetic and Harmonic	Attractive	Safe and Reliable	Individual and Unique	Simple and Clean	High-End and Luxury
B1	−0.085	−0.077	−0.088	−0.072	−0.071	−0.031	−0.077
B2	−0.015	−0.014	−0.016	−0.013	−0.013	−0.006	−0.014
B3	0.158	0.144	0.165	0.135	0.133	0.059	0.144
B4	−0.047	−0.043	−0.049	−0.04	−0.039	−0.017	−0.043
B5	−0.301	−0.275	−0.313	−0.257	−0.252	−0.112	−0.275
B6	−0.212	−0.193	−0.221	−0.181	−0.178	−0.079	−0.193
B7	−0.374	−0.342	−0.389	−0.319	−0.314	−0.139	−0.341
B8	−0.284	−0.259	−0.295	−0.242	−0.238	−0.105	−0.259
B9	0.157	0.144	0.164	0.134	0.132	0.058	0.144
B10	−0.057	−0.052	−0.059	−0.048	−0.048	−0.021	−0.052
B11	−0.086	−0.078	−0.089	−0.073	−0.072	−0.032	−0.078
B12	−0.022	−0.02	−0.022	−0.018	−0.018	−0.008	−0.02
B13	0.221	0.202	0.23	0.189	0.185	0.082	0.202
B14	−0.206	−0.188	−0.214	−0.176	−0.173	−0.076	−0.188
B15	0.168	0.153	0.175	0.144	0.141	0.062	0.153
B16	0.068	0.062	0.071	0.058	0.057	0.025	0.062
B17	0.249	0.227	0.259	0.213	0.209	0.092	0.227
B18	**0.273**	**0.249**	**0.284**	**0.233**	**0.229**	**0.101**	**0.249**
B19	0.18	0.164	0.187	0.154	0.151	0.067	0.164
B20	0.238	0.217	0.248	0.203	0.199	0.088	0.217
B21	−0.026	−0.023	−0.027	−0.022	−0.021	−0.009	−0.023
Regression Coefficients between Kansei Word Groups and Form Elements in the Top View							
	Comfortable and Pleasant	Aesthetic and Harmonic	Attractive	Safe and Reliable	Individual and Unique	Simple and Clean	High-End and Luxury
C1	−0.061	−0.057	−0.064	−0.049	−0.052	−0.024	−0.057
C2	0.001	0.001	0.001	0.001	0.001	0	0.001
C3	0.126	0.117	0.133	0.101	0.106	0.05	0.117
C4	−0.03	−0.028	−0.032	−0.024	−0.025	−0.012	−0.028

Table 5. *Cont.*

Regression Coefficients between Kansei Word Groups and Form Elements in the Top View							
	Comfortable and Pleasant	**Aesthetic and Harmonic**	**Attractive**	**Safe and Reliable**	**Individual and Unique**	**Simple and Clean**	**High-End and Luxury**
C5	−0.294	−0.273	−0.309	−0.235	−0.247	−0.117	−0.273
C6	−0.213	−0.198	−0.224	−0.17	−0.179	−0.085	−0.198
C7	−0.406	−0.378	−0.426	−0.325	−0.342	−0.161	−0.378
C8	−0.308	−0.287	−0.324	−0.247	−0.259	−0.122	−0.287
C9	0.196	0.183	0.206	0.157	0.165	0.078	0.183
C10	−0.075	−0.069	−0.078	−0.06	−0.063	−0.03	−0.069
C11	−0.052	−0.049	−0.055	−0.042	−0.044	−0.021	−0.049
C12	−0.045	−0.042	−0.048	−0.036	−0.038	−0.018	−0.042
C13	0.222	0.207	0.233	0.178	0.187	0.088	0.207
C14	−0.191	−0.178	−0.201	−0.153	−0.161	−0.076	−0.178
C15	0.181	0.168	0.19	0.145	0.152	0.072	0.168
C16	0.09	0.083	0.094	0.072	0.075	0.036	0.083
C17	**0.237**	**0.22**	**0.249**	**0.19**	**0.199**	**0.094**	**0.22**
C18	0.236	0.22	0.248	0.189	0.199	0.094	0.219
C19	0.176	0.164	0.185	0.141	0.148	0.07	0.164
C20	0.227	0.211	0.238	0.181	0.191	0.09	0.211
C21	−0.016	−0.015	−0.017	−0.013	−0.013	−0.006	−0.015

Table 6. Regression Relationships between Kansei Word Groups and Colors. The highest positive values in the table are shown in bold.

Regression Coefficients between Kansei Word Groups and Colors								
	Comfortable and Pleasant	**Aesthetic and Harmonic**	**Green and Eco-Friendly**	**Attractive**	**Safe and Reliable**	**Individual and Unique**	**Simple and Clean**	**High-End and Luxury**
D1 White	−0.067	−0.097	0.031	−0.19	0.023	−0.164	0.071	−0.238
D2 Black	0.017	0.025	−0.008	0.048	−0.006	0.041	−0.018	0.06
D3 Black and White	**0.107**	**0.156**	−0.051	**0.305**	−0.038	**0.263**	−0.114	**0.383**
D4 Yellow and White	−0.062	−0.09	0.029	−0.176	0.022	−0.151	0.066	−0.22

Through the regression analysis of the relationships between the form elements and Kansei word groups across the three main views (front view, right view, and top view), it was found that form elements A13 in the front view, B18 in the right view, and C17 in the top view had the highest positive regression coefficients. This indicated that the participants perceived these three form elements most strongly and that these elements had a positive correlation with the eight Kansei word groups. The black-and-white line drawings corresponding to A13, B18, and C17 are shown in Figure 6.

In the table showing the relationships between color attributes and Kansei word groups, it can be observed that participants' perceptions were strongest when the product color included black and white or was purely white.

In the table showing the relationship between material attributes and Kansei word groups, it was evident that when the material was a combination of glass and plastic, the participants' perceptions were the most pronounced.

Table 7. Regression Relationships between Kansei Word Groups and Materials. The highest positive values in the table are shown in bold.

Regression Coefficients between Kansei Word Groups and Materials								
	Comfortable and Pleasant	**Aesthetic and Harmonic**	**Green and Eco-Friendly**	**Attractive**	**Safe and Reliable**	**Individual and Unique**	**Simple and Clean**	**High-End and Luxury**
E1 Plastic	0.018	0.015	0.021	0.016	0.021	0.017	0.006	0.015
E2 Metal and Plastic	−0.212	−0.174	−0.247	−0.187	−0.244	−0.194	−0.073	−0.176
E3 Wood and Plastic	0.254	0.208	0.296	0.223	0.292	0.232	0.088	0.21
E4 Glass and Plastic	**0.372**	**0.305**	**0.434**	**0.328**	**0.428**	**0.34**	**0.129**	**0.309**
E5 Wood Metal and Plastic	−0.335	−0.275	−0.391	−0.295	−0.386	−0.307	−0.116	−0.278

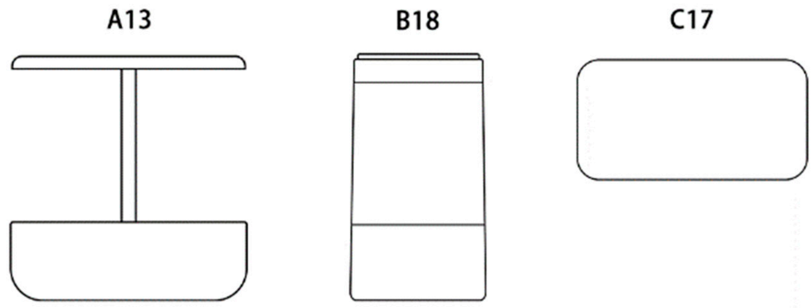


Figure 6. Black-and-White Line Drawings Corresponding to A13, B18, and C17.

4.3.2. Constructing the Optimal Design Solution

Through the above analysis of product morphology and the results of the PLSR predictive model, we identified the design elements with the highest positive correlation coefficients with Kansei words among the three main appearance elements (form, color, and material) of indoor hydroponic products. Incorporating the 62 representative product images obtained during the initial image processing stage of the experiment, we attempted to construct an optimal hypothetical design solution for the appearance of indoor hydroponic products. This is presented in the form of one-dimensional black-and-white sketches. Two types of sketches were created: one without cultivation holes, intended for subsequent product and plant generation, and another with cultivation holes, intended for generating only the product. Both sketches are shown in Figure 7, with images set against a pure white background and a resolution of 512 × 512 pixels.

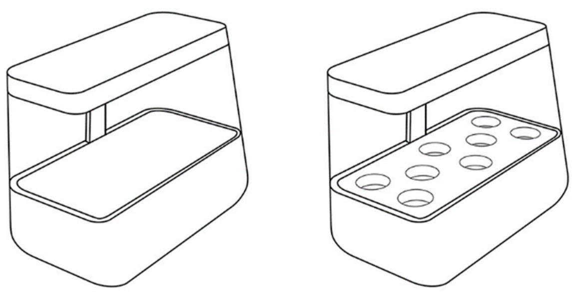


Figure 7. Two Types of One-Dimensional Black-and-White Sketches.

The purpose of constructing the hypothetical optimal design solution is to add control conditions to the images during subsequent AI image generation, ensuring that the AI-generated images closely resemble the results obtained from the predictive model. This approach promotes the final evaluation of the entire process.

4.4. AI Image Generation

The version of SD used in this study is based on the checkpoint model sd_xl_base_1.0.safetensors (https://huggingface.co/stabilityai/stable-diffusion-xl-base-1.0/blob/main/sd_xl_base_1.0.safetensors, accessed on 8 August 2024) and the variational autoencoder sdxl_vae.safetensors (https://huggingface.co/stabilityai/sdxl-vae/blob/main/sdxl_vae.safetensors, accessed on 8 August 2024), using CLIP encoding. First, to assess SD's understanding of indoor hydroponic products, we conducted an initial check using prompt keywords such as 'household indoor hydroponics' and 'home plant cultivation'. The results are shown in Figure 8.

Figure 8. SD-Generated Household Indoor Hydroponic Products.

The results shown in the figure indicated that using SD with only input prompts cannot accurately generate this type of product. Although the product appearance in the images seemed somewhat accurate, certain details were highly unreasonable, and there were significant differences compared to the product appearance studied in this research. Therefore, in this stage, it was necessary to add a custom-trained LoRA model to SD to assist in generating the desired images.

First, an image training set needs to be prepared. Based on the PLSR model's predictive results, we had obtained the elements that users expect in the product appearance. After screening the 54 product images, we retained 28 images from seven products taken from different angles that matched the form, color, and material elements identified by the PLSR model. The following tests confirmed that the LoRA training set, consisting of 28 images, was sufficient to achieve the desired results.

The training employed the LoRA Scripts framework (https://github.com/Akegarasu/lora-scripts, accessed on 8 August 2024) to train an LoRA model based on sd_xl_base_1.0.safetensors. After continuous parameter tuning, the learning rate was set to 1×10^{-4}, with a decay strategy using the cosine_with_restarts scheduler. The training was conducted over 10 epochs with a batch size of 1, ensuring that the model could effectively learn from the dataset while managing memory constraints. Gradient accumulation was enabled with a step size of 1, meaning the model updated its weights every batch. Gradient checkpointing was also utilized to reduce memory usage during training. To accommodate varying image sizes, the training process employed a bucket resolution technique, setting the minimum and maximum resolutions to 256×256 and 1024×1024 pixels, respectively. This allowed the model to adapt to different image dimensions while maintaining consistent performance. The prior loss weight was set to 1, and multiple noise iterations were configured to adjust the noise application during training, enhancing the model's robustness. For model optimization, the AdamW8bit optimizer was used, leveraging mixed precision with BF16 to accelerate training while maintaining numerical stability.

After completing the training, SD was accessed again with the same initial parameters used for testing, but with the new LoRA model added. A total of eight images were generated in two sets, each containing four images. One set displayed only the product without plants, showcasing the product itself, while the other set included plants to demonstrate the product's function. The generated images are shown in Figure 9, with all images set against a pure white background and to a resolution of 512×512 pixels.

Figure 9. Image Outputs with LoRA Added.

Based on the newly generated image results, it can be observed that, after adding the LoRA model, SD was able to capture the appearance of indoor hydroponic products from different angles. However, the generated shapes still exhibited randomness and did not align with the black-and-white sketches derived from the PLSR predictive model. Moreover, the material choice did not prominently feature glass, as expected. Therefore, further optimization and improvement of the images were necessary.

Condition-Controlled Image Generation

To ensure that the generated product images have a similar form to the black-and-white sketches obtained through the PLSR predictive model and that they prominently display the glass material option, the sketches from Figure 8 were used as conditional controls and were added to the ControlNet plugin suitable for SD, with the lineart function selected to colorize these black-and-white sketches. Additionally, the trained LoRA model was used, and more comprehensive prompt keywords were inputted to enhance the accuracy of the generated images. Finally, a total of 160 product renderings were generated, including 40 sets, each containing 4 images. Among these, 80 images displayed only the product itself without plants, and 80 images demonstrated the product's functionality with plants. After discussion and filtering, 20 final images were selected and sequentially numbered, as shown in Figure 10. All images have a resolution of 512 $\times$ 512 pixels. Occasionally, the final output images had cluttered backgrounds, so to achieve a uniform visual effect, a white background was used for all images.

From the final output images, it can be observed that although there are occasional minor inconsistencies in the details, the product appearance images generated after training and adding conditional controls have nicely reproduced the optimal design scheme constructed by the predictive model. This is not only reflected in the high similarity between the appearance and the black-and-white sketches but also the consistency with the PLSR results in terms of color matching and materials through the precise input of prompts.

4.5. Evaluation

To verify whether the two-dimensional colored sketches of the product design solutions obtained through the above process are satisfactory, the final generated images underwent two rounds of evaluation.

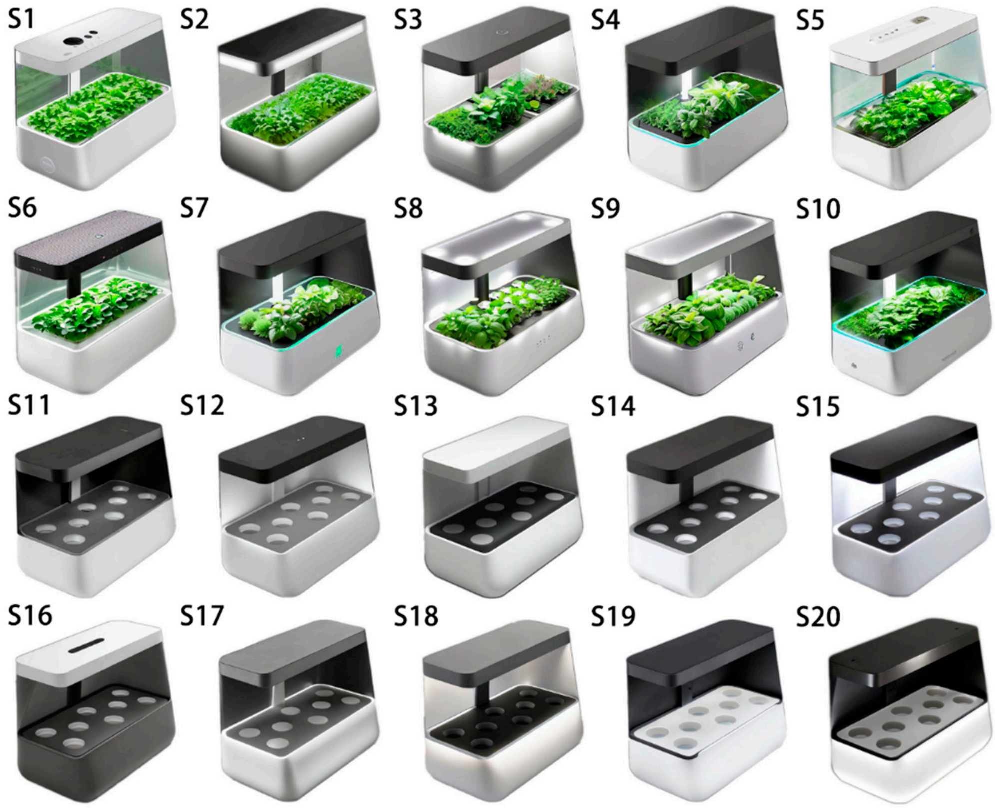


Figure 10. 20 Final Renderings, numbered sequentially as S1–S20.

4.5.1. Evaluation 1

First, the evaluation was conducted using the 20 AI-generated images shown in Figure 11. The evaluation criteria were based on the eight Kansei word groups identified earlier. We continued using a 5-point Likert scale for the questionnaire. For example, considering the Kansei word group Comfortable and Pleasant', the participants were asked to rate the relationship between the images and the Kansei words. A score of 1 indicated that the product image could not evoke the participants' perception of the word group, 2 indicated it rarely could, 3 was neutral, 4 indicated it somewhat could, and 5 indicated that it could evoke the participants' perception of the word group. A total of 192 participants took part in this evaluation. The final results are shown in Table 8.

Table 8. Mean Scores Between Generated Images and Kansei Word Groups.

Mean Scores Between Generated Images and Kansei Word Groups							
Comfortable and Pleasant	**Aesthetic and Harmonic**	**Green and Eco-Friendly**	**Attractive**	**Safe and Reliable**	**Individual and Unique**	**Simple and Clean**	**High-End and Luxury**
3.99	4.03	3.96	3.92	4.14	3.75	4.43	4.08

This evaluation provided a simple scoring of the relationship between the AI-generated images and the Kansei word groups. Based on the perceptions of the 192 participants, the indoor hydroponic product images generated through the above process received average scores of around 4 (somewhat satisfactory). This result indicated that, despite many details not being fully displayed in the images, the product appearance alone was sufficient to evoke a positive psychological response from users.

4.5.2. Evaluation 2

Next, an evaluation was conducted comparing the AI-generated images with existing products on the market. We selected the initial six representative appearance images, as shown in Figure 6, and chose the AI-generated image S15 without plants as the sample for comparison because its product form, color, and material closely align with the optimal design solution. A total of seven images were used as evaluation subjects for this comparison, as shown in Figure 11.

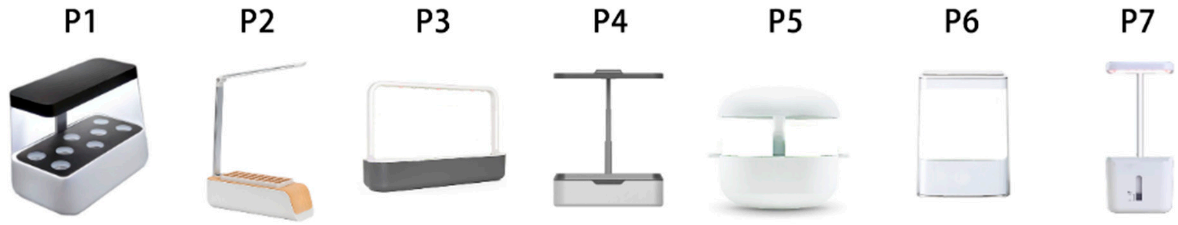
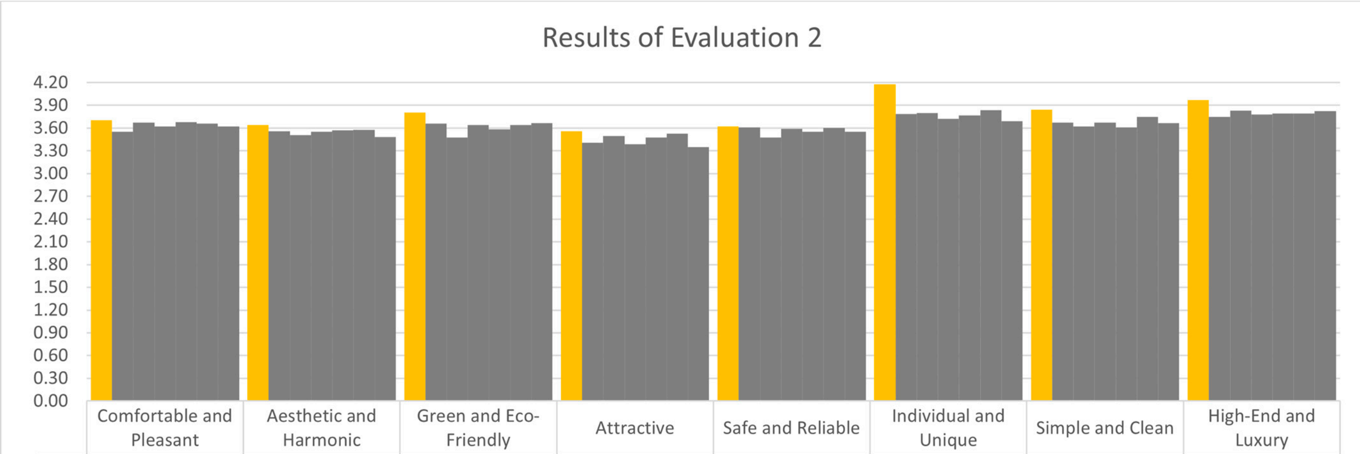


Figure 11. The seven Images Involved in the Evaluation, numbered sequentially as P1–P7.

The evaluation criteria remained the eight Kansei word groups, using a 5-point scale to assess the relationship between the images and the Kansei word groups. The participants were the same 192 individuals who participated in the first round of image evaluation. An example of the questionnaire for the word group 'Comfortable and Pleasant' is shown in Figure 12. The results of Evaluation 2 are presented in Figure 13, where the data for AI-generated images are highlighted in yellow, and the data for existing product images are marked in gray.

Figure 12. Questionnaire Example Using 'Comfort and Pleasure'.



	Comfortable and Pleasant	Aesthetic and Harmonic	Green and Eco-Friendly	Attractive	Safe and Reliable	Individual and Unique	Simple and Clean	High-End and Luxury
p1	3.70	3.64	3.81	3.56	3.62	4.18	3.84	3.97
p2	3.55	3.56	3.66	3.41	3.61	3.79	3.67	3.75
p3	3.67	3.51	3.48	3.49	3.48	3.80	3.62	3.83
p4	3.62	3.55	3.64	3.39	3.59	3.72	3.67	3.78
p5	3.68	3.57	3.59	3.48	3.55	3.76	3.61	3.79
p6	3.66	3.58	3.64	3.53	3.60	3.84	3.75	3.79
p7	3.62	3.49	3.66	3.35	3.55	3.69	3.66	3.82

Figure 13. Results of Evaluation 2.

From the results of Evaluation 2, it can be observed that the AI-generated images scored higher than the existing market products across all Kansei word groups, with particularly outstanding performance in the 'Individual and Unique' category. This suggests that the AI-generated product appearance possesses distinctive features that set it apart from existing products.

Combining the results of both evaluations, it is evident that the AI-generated product images are satisfactory, meeting users' emotional needs while also offering advantages in various attributes compared to existing market products.

5. Discussion

This study combines Kansei engineering as a theoretical foundation with AI image generation technology and other methods, using household indoor hydroponics as the research subject. The focus is on how to efficiently and reasonably explore users' emotional and aesthetic needs for product appearance using scientific and advanced research methods and how to translate these needs into product appearance design elements to generate design solutions.

First, we leveraged the advantages of the internet by using web crawlers to extract images and online reviews related to indoor hydroponics. After a series of filtering processes, the necessary product samples and users' Kansei needs were preliminarily constructed, as shown in Figure 4 and Table 2. This approach significantly improves the efficiency of Kansei data extraction in the initial stages compared to traditional Kansei engineering methods, such as surveys, interviews, focus groups, and literature reviews, which are time-consuming and subjective. Further dimensionality reduction of Kansei words was achieved through Factor Analysis, identifying eight factors with the highest user focus, which were named based on the meanings of the included words to form eight Kansei word groups, as shown in Table 4. This approach not only reasonably identified Kansei words but also reduced the limitations caused by subjectivity. Second, combining product morphology with Partial Least Squares Regression (PLSR), we deconstructed and encoded product forms (front view, side view, and top view), colors, and materials to build and quantify the mapping relationship between the semantic and property spaces, as shown in Tables 5–7, resulting in the optimal design solution shown in Figure 8. Compared to traditional Kansei engineering, which often relies on the designer's subjective judgment, this approach provides a more rational and convincing product design solution. In many previous studies, the process often concluded with black-and-white sketches or text descriptions of the design solutions. However, compared to these, two-dimensional images closer to real products are more comprehensible for users and designers, offering better guidance for final product design. In the final stage of this study, AI image generation based on Stable Diffusion (SD) was used. By incorporating a custom-trained LoRA model and using ControlNet to apply the black-and-white sketches derived from product morphology and PLSR as image controls, two-dimensional colored sketches of indoor hydroponic products were generated, as shown in Figure 10. The generated images underwent two rounds of evaluation. The first evaluation involved 20 AI-generated images with added control conditions, assessed against the 8 Kansei word groups, with the results indicating that the images effectively elicited positive psychological responses from users, as shown in Table 8. The second evaluation compared AI-generated images with existing products, with the results presented in Figure 13, demonstrating that AI-generated images with added control conditions scored higher across all Kansei word groups than existing market products. Combined, these evaluations showed that the product images generated through the above process are reasonable and satisfactory.

The proposed product appearance design process based on Kansei engineering theory, AI image generation, and other methods significantly improves the efficiency of identifying users' Kansei needs while ensuring accuracy and objectivity. It also explores how to apply reasonable methods to add condition controls during AI image generation, allowing for the mass production of product appearance concept sketches that meet user needs. Compared to designs generated purely by designers or sketches produced without condition controls using AI image generation alone, this approach offers greater objectivity, rigor, and accuracy. This not only greatly improves the overall efficiency and rationality of product appearance analysis and design processes but also addresses the critical limitation in traditional Kansei engineering of not being able to directly generate product images, providing valuable guidance for final product design.

Despite these advancements, there exist limitations and areas for further discussion: (1) In constructing the optimal design sketches, although morphology analysis and PLSR were used to identify optimal design elements, the assembly of these elements into black-and-white sketches still required researchers to use personal experience for element combination and sketch drawing, introducing some subjectivity. Therefore, whether there are more rational and objective methods, such as automatically generating sketches based on data through a system, still warrants further discussion and research. (2) The generated product images only consider the general appearance, resulting in missing details that reduce the overall realism of the images. Product textures and plant details in the images also displayed some inconsistencies, and the final images were presented from only one angle. These factors may also introduce more unfavorable elements during image evaluation, leading to incomplete testing. Therefore, in future research, whether displaying the product from different angles, further refining the sketches, and modifying the prompts can result in more realistic and comprehensive image presentations—thereby enhancing the completeness of the testing and increasing the credibility of the experiment—requires further validation over time. (3) Although product appearance attributes are crucial, other aspects such as functionality are equally important, and this study does not address these additional factors. To fully design an excellent product, further research into other product attributes is needed. (4) This study only used SD WebUI for generating and exploring product appearance images, which presented a certain limitation in terms of singularity. However, in the context of technological advancements, there are many other excellent image-generation tools available. Due to differences in their underlying logic, these tools may produce varying image outputs. Therefore, comparing the results of different generation tools in future research can enhance the diversity of AI image generation in product design and facilitate a more comprehensive development of this method across different fields. (5) Although the proposed process and methods in this study provided valuable guidance, the research was conducted using only indoor hydroponic products as the research subject, which resulted in a lack of diversity in the product samples. Therefore, future research needs to further explore whether this approach can be applied to other products, such as those with more complex forms or different product types. Enhancing research and comparisons across various products can better support the comprehensive development of this method or similar approaches.

6. Conclusions

In the context of sustainable development, quickly and accurately understanding users' emotional and aesthetic needs for products and quickly translating these needs into product design elements are key factors in enhancing the overall efficiency of the product design process, increasing product competitiveness, and promoting product sustainability. However, how to accurately, reasonably, and efficiently achieve product appearance designs that meet users' Kansei needs and how to improve design efficiency through reasonable methods remain ongoing challenges for designers and companies. This paper proposes a product appearance design process based on Kansei engineering theory and AI image generation technology, among other methods. The contributions and guiding significance are summarized as follows:

Contribution 1: Based on the theoretical foundation of Kansei engineering, this study leveraged the advantages of the internet and scientific research methods, such as the web crawler and online review mining, to improve the efficiency of constructing user Kansei needs in the early stages. Using Factor Analysis, the study objectively explored users' Kansei needs, reducing the adverse effects of subjective factors.

Contribution 2: By applying AI image generation technology based on Stable Diffusion (SD) to product appearance design, the study significantly improved the timeliness of constructing design solutions by producing a greater number and higher quality of sketch options, thereby enhancing the overall efficiency of the product design process.

Contribution 3: By combining product morphology with mathematical models, we quantified the relationship between users' Kansei needs and product appearance and used this information as conditional controls to constrain the results of AI image generation. This approach not only reasonably generated design sketches but also significantly addressed the instability and inaccuracies associated with AI-generated images. This provided a rational guiding approach for future work that aimed to apply AI image generation technology to the field of product design.

Contribution 4: Selecting household indoor hydroponics—an emerging product with green and sustainable attributes—as the research subject not only validated the rationality of the proposed design process but also filled a gap in the appearance design field for this product, contributing to its comprehensive development in the future.

Guiding Significance: The product appearance design process proposed in this study guides designers and companies in related fields on how to utilize new resources and technologies brought about by sustainable development within the product design process to improve design efficiency, enhance product competitiveness and sustainability, and expand new ideas on integrating these resources and technologies with scientific research methods.

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Appendix A

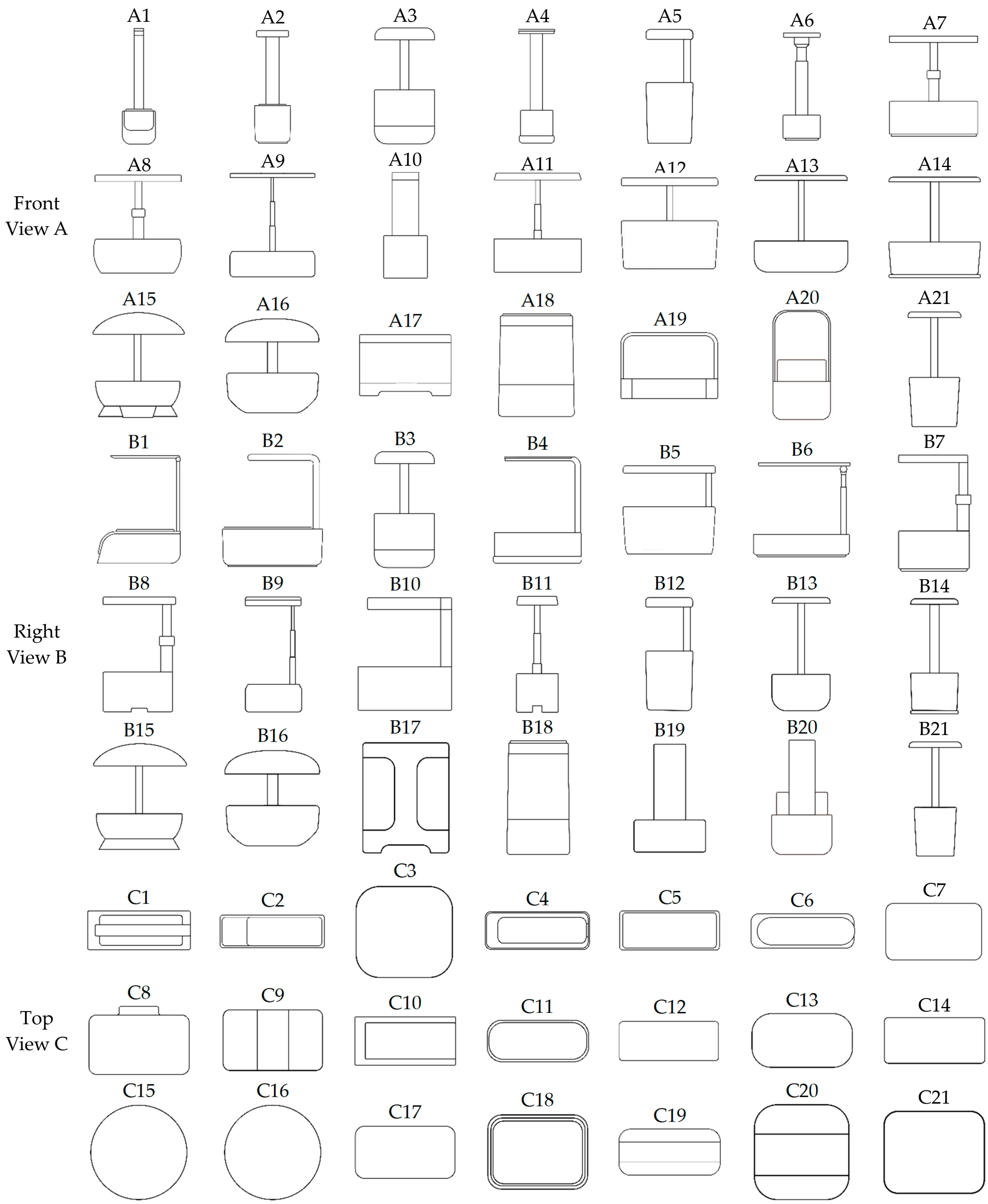

Figure A1. Front View, Right View, and Top View of Product Deconstruction.

Appendix B

Table A1. Front View, Right View, and Top View of Product Deconstruction.

	Color				Material				
Product ID	**D1 White**	**D2 Black**	**D3 Black White**	**D4 Yellow White**	**E1 Plastic**	**E2 Metal Plastic**	**E3 Wood Plastic**	**E4 Glass Plastic**	**E5 Wood Metal Plastic**
1	0	0	0	1	0	0	0	0	1
2	1	0	0	0	1	0	0	0	0
3	1	0	0	0	1	0	0	0	0
4	1	0	0	0	1	0	0	0	0
5	1	0	0	0	0	1	0	0	0
6	1	0	0	0	0	1	0	0	0
7	0	0	0	1	0	0	0	0	1
8	1	0	0	0	0	1	0	0	0
9	0	0	1	0	0	1	0	0	0
10	1	0	0	0	1	0	0	0	0
11	0	0	1	0	0	1	0	0	0
12	1	0	0	0	1	0	0	0	0
13	0	0	1	0	0	1	0	0	0
14	0	0	0	1	0	0	0	0	1
15	1	0	0	0	0	0	0	1	0
16	0	0	1	0	1	0	0	0	0
17	1	0	0	0	0	0	0	1	0
18	1	0	0	0	0	0	0	1	0
19	0	0	0	1	0	0	1	0	0
20	0	0	0	0	0	0	1	0	0
21	0	1	0	0	1	0	0	0	0

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