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Research Article

Analysis of pairings of colors and materials of furnishings in interior design with a data-driven framework

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Abstract

Color–material furnishing pairing is known as a “black-box” for interior designers. The overall atmosphere of a space can be changed by modifying furnishing combinations, e.g., to express modern or classic styles. Designers carefully choose pairings of colors and materials that fit their intended interior design styles based on experience and knowledge. However, no specific principles or rules have yet been established. Therefore, this study aims to derive a furnishing pairing principle based on a novel framework comprising object detection, color extraction, material recognition, and network analysis. We used the proposed framework to analyze large-scale interior design image data ($N = 24194$) collected from an online interior design platform. We also used the authenticity algorithm to analyze the relative influence of styles. By using the data-driven method from large-scale data in each of the eight interior styles, we derived authentic color, material, and furnishing combinations. Our study results revealed that images with high authenticity values in each style matched existing style descriptions. Additionally, the proposed framework allows interior style image retrieval based on a specific color, material, and furnishing combination. Our findings have implications for research on the development of style-aware furniture retrieval systems and automatic interior design generation methods.

Keywords: computational design, data-driven design, interior design, furniture pairing, color and material analysis, style analysis

1. Introduction

In recent years, the size of the interior design market has increased worldwide, along with a growing interest in interior design. According to the Statista market research platform, the global interior design market has grown by approximately $50 billion between 2013 and 2021 (Statista, 2021). In particular, the number of online furniture purchases increased (News Channel 21, 2022) because interest in do-it-yourself (DIY) interiors has grown as the time spent at home has increased because of the impact of COVID-19. The global DIY home decor market is expected to continue to grow (Allied Market Research, 2022). Space owners obtain information about DIY interior know-how and gain much knowledge through various online interior magazines (Good Housekeeping, 2022). Space owners take on the role of semi-expert interior designers in decorating their houses.

Interior design can be broadly divided into two components: space and home furnishings. Furniture affects the feeling of satisfaction associated with a given space (Kim & Kim, 2019), with home furnishings among the most important elements of the interior design process (Singh & Sharma, 2016). Designers consider the combination of furnishings to change the overall atmosphere of a space. Additionally, color and material provide diverse feelings toward the product (Park *et al.*, 2015). Thus, harmonizing interior design by understanding the importance of color, shape, and texture in interior design is essential (Anderson, 2014). Interior design aesthetics are expressed by harmonious combinations of design elements such as colors and materials of furnishings.

However, in the interior design process, selecting pairings of furnishings depends on experts’ experience and intuition. Therefore, there are no specific principles or rules, and various difficulties arise in interior design processes. For example, many people choose furnishings from online interior design platforms. Most such interior design online platforms (e.g., ikea.com, ohou.se/store), provide information on furnishings that includes space used, furniture type, color, material, size, brand, and price. This information is only provided based on the characteristics of the furnishing itself. Because most space owners lack relevant experience in interior design, selecting furniture combinations that exactly match the desired style to express an overall atmosphere is generally quite difficult.

Ultimately, to increase the overall efficiency of interior design processes, an improved understanding of interior design is needed. Furthermore, it is crucial to understand how styles express design directions in the design process (Hyun & Lee, 2018) because design styles are a unique pattern observed throughout the design process and can be understood as representing the characteristics of the design elements (Chan, 2000; Hyun *et al.*, 2015). However, pairings of design elements that can define a given style have not been explicitly established. Therefore, design style studies have analyzed authentic pairings of design elements to understand the design process from various fields (Strobbe *et al.*, 2016; Yi *et al.*, 2020). Accordingly, finding an authentic pairing of

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design elements that make up an interior style is a key task in the design process. Interior styles are composed by combining different design elements such as colors and materials of furnishings. From this viewpoint, some studies have considered the colors and materials of furnishings as the interior design element (Chen *et al.*, 2015, 2016).

However, previous analyses have focused only on the characteristics of design elements observed in a given style, and failed to consider the relationship between design elements. Hence, in this paper, we propose to derive pairings of furnishings based on a novel data-driven framework that we developed. Specifically, we identified relationships between furnishing elements relevant to interior design and attempted to determine suitable authentic pairings of colors and materials. The framework comprises object detection, color extraction, material recognition, and network analysis. We used the proposed data-driven framework to analyze a large-scale dataset of interior design images ($N = 24\,194$) collected from an online interior design platform. The recent availability of large-scale interior image data has led to a systematic understanding of interior design through quantitative analysis. In prior research, network analysis using large-scale data has facilitated new approaches to abstract fields that were difficult to explain (Ahn *et al.*, 2011; Park *et al.*, 2015). Therefore, we conducted network analysis to identify interior styles based on authentic pairings of colors and materials, aiming to enhance understanding of the interior design process. The following tasks are performed to achieve the goals of this study:

- (i) Large-scale image data containing eight interior styles were collected from the online interior design platform "Today's House" (ohou.se).
- (ii) Object detection, color extraction, material recognition, and segmentation were performed on the image data, and the results were extracted into a color–material matrix.
- (iii) The obtained results were then converted into a data format suitable for analysis of authentic color and material pairings.
- (iv) Through network analysis, we reveal the authentic color and material pairings of furnishings in eight interior styles.
- (v) The most authentic interior style images were then extracted for each style through authentic style image scoring.

2. Related Work

2.1. Interior design style

The design style represents a specific design method, or a unique form shown, and can be identified by understanding the unique characteristics of design elements inherent in the style (Chan, 2000; Hyun *et al.*, 2015; Ostrosi *et al.*, 2019). Moreover, style reveals the design direction for space owner, and identifies that similar design plays an important role in the strategic design process (Hyun *et al.*, 2015). In this sense, the style represents overall design atmosphere in interior design process. Chan (2000) noted that combinations of design elements could be used to examine architectural styles. Therefore, the interior style consists of combining design elements. As the definition of interior design style is mainly in the domain of experts, the universal pairing of interior style elements is not known. Therefore, many researchers have conducted studies to determine authentic pairing of design elements to identify a design style. For example, Yi *et al.* (2020) proposed a method for recognizing house-style images using a deep convolutional neural network (CNN). They classified and trained 17 styles of American house images using house elements, such as roofs and doors. Strobbe *et al.* (2016) used machine learning to learn the two-dimensional (2D) floor plans of specific architectural examples and proposed a method to classify other images. They analyzed the authentic architectural style through the topological relationship using the spatial elements of the 2D floor plan.

Previous studies have analyzed design styles using authentic design elements. In this respect, the authentic pairing of design elements is essential for the analysis of style in the interior design process. Furthermore, because interior design style influences user experience in terms of space, determining the interior design style is a key task in this regard. In addition, home furnishing is a crucial element of the interior design process, and interior design consists of various furnishings (Singh & Sharma, 2016; Weiss *et al.*, 2020).

Therefore, prior studies have been conducted to analyze or recommend furnishings in interior styles. For example, researchers have used deep learning (DL) to learn the properties of furniture images to create and recommend new furniture to match a desired style (Singh & Sharma, 2016; Weiss *et al.*, 2020). Although these models were trained using furniture images, they could not establish universality of the style because they relied on source data from only a few experts to determine styles. Also, the authentic pairing of design elements in terms of style could not be analyzed considering the relationship between furnishings. Tautkute *et al.* (2017) proposed a multimodal search framework that synthesized object detection, visual search, and text queries through style-related metadata to derive a list of furniture results similar in appearance and style using an IKEA dataset. However, their system did not specifically categorize images as expressing specific interior styles. They only considered the use of text values to describe design elements of style, such as "cozy" or "soft," and ignored the relationship between furnishings.

All of these prior works lack analyzing design style in terms of the relationship between design elements. In this context, to analyze the interior design style, we consider the relationship between the furnishings used and quantitatively analyze the specific design elements of the furnishing in our study.

2.2. Interior design elements

Choosing a style and furniture to fit a given style is a key task in interior design. Additionally, styles can be explained by analyzing pairings of furnishing design elements. Various studies have been conducted on interior design elements by dividing them into three components: furnishing, color, and material. Most studies on the interior design process have recommended choosing colors in the furnishing stage (Chen *et al.*, 2016; Umezu & Takahashi, 2017; Zhu *et al.*, 2017; Weiss *et al.*, 2020) or considered the color and material of furnishings (Chen et al, 2015; Ogino, 2017). Therefore, finding authentic pairings of colors and materials of furnishings is necessary for understanding different interior styles.

Among interior design elements, color largely determines the sense of a space and influences occupants' emotions and behaviors (Haller, 2017; Umezu & Takahashi, 2017; Cao, 2018). Because all interior elements have color, color tone affects the overall interior design. Additionally, as product design becomes more critical for consumer decision-making (Park *et al.*, 2015; Misaka & Aoyama, 2018), product designers appeal to consumers' senses through materials with technical and sensorial properties (Karana *et al.*, 2008). Product designers are prudent in their selection of materials because materials affect the way a product is perceived (Arabe, 2004). Several methods have been developed to automatically generate materials for interior spaces based on their importance (Liu et al., 2019; Zhang *et al.*, 2019). Additionally, materials are a mixture of color and texture, with color as a critical factor for material recognition (Liu *et al.*, 2010; Sandid & Douik, 2016). Therefore, harmonious combinations of colors and materials are typically considered in the interior design process as key elements in furnishing design.

However, distinctions between interior styles remain somewhat unclear (Weiss *et al.*, 2020) and selecting a harmonious pairing of interior design elements is challenging because it depends on the designer's experience (Zhu *et al.*, 2017). In this context, various studies exploring harmonious interior elements have focused on recommending and creating furnishings of various colors and materials in interior design process. For example, Chen *et al.* (2016) trained a Bayesian network to recognize color data for 14 furniture types on 600 bedroom interior images corresponding to five styles. To uncover the color interdependence of the different furniture in each style, they trained a tree-augmented naïve Bayesian network using style nodes and furniture-type nodes to identify color pairings suitable for designing a 3D model. However, they used only representative colors for each type of furnishing and did not consider the color relationship of the furnishings in the image. Furthermore, their method was unable to assume the various characteristics of furnishings by randomly assigning materials. Finally, because they limited the model to five clustering centers for each furnishing type in terms of style, it was difficult to evaluate all color pairings quantitatively. Meanwhile, Chen *et al.* (2015) presented a system designed to automatically generate material proposals in a specific 3D interior scene by using interior furnishings and image datasets of interior scenes. Using global aesthetic rules intended to describe overall color harmony and the local material rules learned from potential combinations of materials, they predicted materials in the image using a color compatibility model and suggested materials. They analyzed only five representative colors from the entire set of interior images. Additionally, they did not analyze style by considering interior elements pairing, including both color and material in the furnishing stage.

In summary, previous literature on interior design style analysis did not analyze the relationship between furnishings and the pairing of authentic design elements; therefore, the understanding of the style in the interior design process was insufficient. In this respect, to understand the ambiguous interior style and increase the efficiency of the interior design process, we analyzed the authentic pairing principle of interior elements (color and material) and furnishing for each interior style.

2.3. Network analysis for large-scale data analysis

As the availability of large-scale data increases, quantitative analysis of abstract topics that are difficult to explain through network analysis has been extensively studied. Network analysis is a method of quantitatively analyzing the structure, diffusion, and evolutionary processes of individuals and groups by modeling their relationships as nodes and links. Because this method focuses on interrelationships, various patterns can be found in large-scale data (Park *et al.*, 2015). Network analysis has provided an opportunity for a new approach by conducting quantitative data analysis in various fields, evaluated based on qualitative criteria.

Ahn *et al.* (2011) created a bipartite network using the ingredients used in cuisine and flavor compounds constituting each ingredient to construct a flavor network with a one-mode projection. They identified relationships between ingredients as shared flavor compounds and discovered new patterns that transcended specific cuisines and ingredients. Furthermore, they presented a quantitative analysis method of ingredient pairing in the field of cuisine, in which creativity is a key requirement. They calculated the authenticity and prevalence of ingredients in each cuisine.

Park *et al.* (2015) constructed a network using 96 000 classical music CDs along with their dates of release and composer information. They analyzed the growth of a bipartite network to confirm relationships between composers of classical music and predicted the future growth of composers. By using a large-scale dataset and performing network analyses of the evolution of cultures over time, they interpreted relationships between new and existing data, and improved the understanding of complex cultural systems.

Previous studies have identified new patterns inherent in large-scale data using network analysis of knowledge in creative fields that were difficult to understand. In this regard, we could use network analysis to discover the design patterns of interior styles. Therefore, this study aims to reveal the principles of color and material pairings in an interior style by forming a network and analyzing the color, material, and furnishing data extracted from interior images.

3. Method

We performed the following task to determine the principles of color and material pairings for furnishings in each style. Section 3 describes the proposed framework, which is divided into two main steps: data processing and data analysis, as illustrated in Fig. 1. As shown in Fig. 1, data processing includes data collection, object detection, color extraction, material recognition, and segmentation, and data matrix projection. In this step, we processed all data for interior image analysis. We then analyzed the color, material, and furnishing using an authenticity algorithm.

3.1. Data processing

Five data processing tasks were performed to analyze colors and materials of furnishing according to interior style (Fig. 2). First, white balance was applied to the interior images to express the true colors (Fig. 2a). Second, we recognized an object in the interior image and saved the detected object image separately, as shown in Fig. 2b. When different object bounding boxes overlapped, as shown in Fig. 2b-1, we cropped the overlapping areas from each stored object image. Third, to detect the object, material segmentation was performed on the entire image and stored in the same size as the original size (Fig. 2c). The material image was segmented by the object image area saved in (Fig. 2d). Fourth, using the segmented material image (Fig. 2d) for each object, the object image (Fig. 2b-1) was segmented for each material area, and the image was stored separately (Fig. 2e). Finally, the color was extracted from the image for each material area of each object and saved (Fig. 2f).

Through this process, a matrix of the color and material of several objects was created and saved in an interior image folder. In the file name of the matrix, the name of the color and material with the highest ratio was added, and each object had a Category 2-digit alphabet and a seven-digit unique number in the order of processing (e.g., yellow-wood-table-kr0000738). We created a matrix that stored each object's color and material ratio (Fig. 2g). Finally, we conducted color and material analysis of the furnishings by using the extracted matrix.

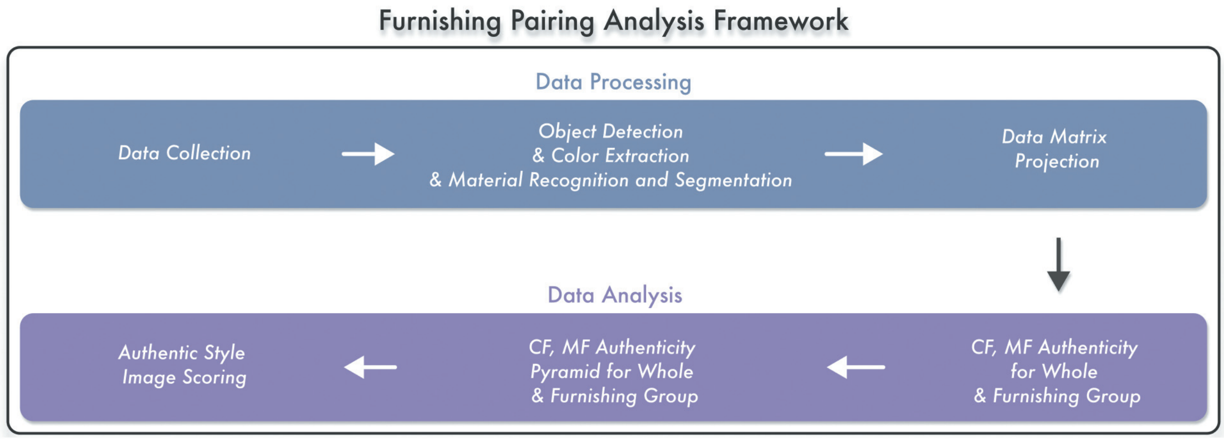

Figure 1: Furnishing pairing analysis framework.

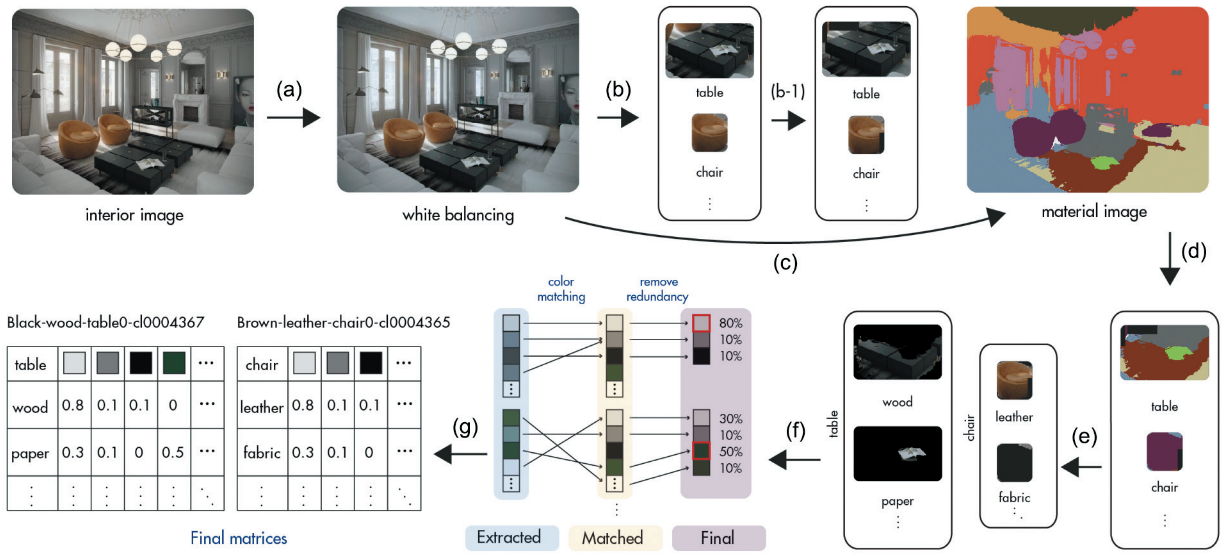

Figure 2: Data processing. (a) Image white balance; (b) object detection; (b-1) overlapping areas crop; (c) material recognition and segmentation; (d) material segmentation; (e) object segmentation by material; (f) color extraction; and (g) matrix generation.

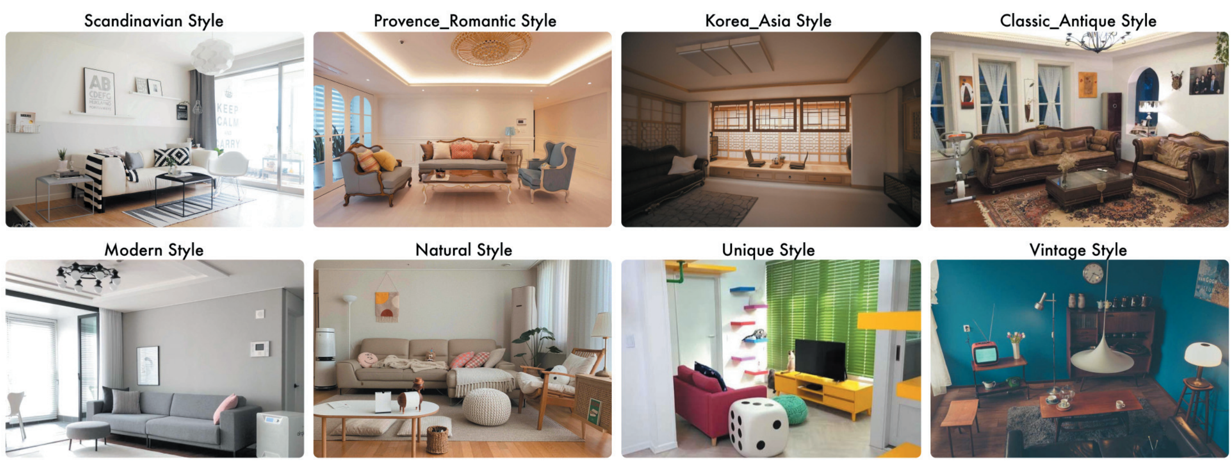

Figure 3: Eight interior style image examples.

Figure 4: Image white balance example. (a) Raw image and (b) image with white balance process.

3.1.1. *Data collection*

In Korea, the living room—located at the center of most houses—serves as the main activity space. Because the living room represents the house, previous interior studies have focused on living rooms (Ogino, 2017; Liu *et al.*, 2019). Therefore, we collected information on actual living-room interior cases shared by residents and experts through the Korean online interior design platform, Today's House.

Today's House is recognized worldwide as the largest online interior platform in Korea and has also made a foray overseas (Business Wire, 2022). Today's House offers eight of its own interior design styles. Today's House data share real interior cases of eight styles selected by users so that we could analyze a more realistic interior design direction. A large dataset, including images and style metadata of actual living-room interior cases, was collected using a custom data crawler. A user uploading an actual example specified the style information corresponding to the interior image.

Today's House users include both experts and non-experts. There are 141 experts and 24053 non-experts in the collected dataset. The expert and non-expert ratio is dramatic; however, this is because Today's House is selective when inviting interior design experts on its platform. Today's House Partner Center reviews the expert's information and proceeds with the expert registration of Today's House (Today's House Partner Center, n.d.). Also, non-expert users in Today's Houses have the purpose of decorating their own houses as semi-experts. Since they share the interior design of their own house with their resources, it is fair to consider them semi-experts. Non-expert users are as interested in interior design as experts. For example, non-expert users collect interior design references such as interior images, and interior design descriptions such as interior know-how, and furniture information by utilizing a feature called "scraping" on the informative pages. We identified that users scraped the interior design reference page with an average of 102.45 (SD = 260.80). The interior design reference page also indicates the interior design style information, whether the design is a Scandinavian or classic style. Additionally, when users share examples of their designs, they must specify what style they are. In this respect, users indirectly expand their knowledge about interior styles by scraping interior design references. Accordingly, we regarded that non-expert users understand the classification of interior styles provided by Today's House.

The interior image included eight styles (Fig. 3): *Natural style*, *Modern style*, *Scandinavian style*, *Vintage style*, *Unique style*, *Classic_Antique style*, *Provence_Romantic style*, and *Korea_Asia style*. We collected 58862 images and filtered them down to 24194 images based on the following conditions:

(i) Images that were difficult to judge as living rooms,
(ii) Images in which the interior process was not completed,
(iii) Images showing too little range, and
(iv) Images with no furnishings.

3.1.2. *Image white balance*

To increase the accuracy of the color extraction and material segmentation processes, we performed a white balance process on the collected living-room interior images. The digital camera sensor identifies the light reflected by an object. Accurately reproducing the colors requires image color correction because the color recognized by the computer is different from that experienced by the human visual system (Hwang *et al.*, 2011).

The white balance method is the simplest image color correction method (Xin *et al.*, 2021). It is largely divided into two types: first, based on hypothetical statistics, and second, based on sample learning. The latter is slow and requires many samples for long-term learning (Xu *et al.*, 2014). Therefore, we used the Gray-World algorithm based on hypothetical statistics proposed by Buchsbaum (1980) for image white balance preprocessing. The Gray-World algorithm is based on the principle that the average reflectance of an image is achromatic (Weng *et al.*, 2005). According to Weng *et al.* (2005), the Gray-World algorithm is the oldest and simplest method among automatic white balance algorithms. The Gray-World algorithm has been used in recent image-correction research. For example, Xu *et al.* (2014) used the Gray-World algorithm for the tongue image color correction method. Ma *et al.* (2019) also used the Gray-World algorithm for underwater image restoration. We could correct the color extracted from the system to be close to the true color by performing a white balance process on the collected interior images, as shown in Fig. 4.

3.1.3. *Object detection and robustness*

We used the You Only Look Once (YOLO) v3 model for object detection (Redmon & Farhadi, 2018). As a simple and fast object detection method, YOLOv3 considers multiple bounding boxes and class probabilities within an image as a single regression problem by using a single CNN. The latest models after YOLOv3 have

Table 1: Precision and recall of 10 class objects.

Object type	Precision	Recall
Floor lamp	0.9630	0.8667
Ceiling light	0.9474	0.8182
Rug	0.9028	0.8784
Plant	0.9024	0.8668
Curtain	0.8926	0.8372
Sofa	0.8901	0.9419
Chair	0.8515	0.7963
Table	0.8396	0.8241
Art wall	0.8215	0.7500
Cabinet	0.7619	0.8000

been released. However, according to Ge *et al.* (2021), YOLOv3 detects faster than YOLOv4 and v5. Additionally, YOLOv3 is still the most widely used in the industry because of insufficient software support for the latest version. The advantages of YOLOv3 have allowed many recent studies to perform object detection (Lee *et al.*, 2021; Singh *et al.*, 2021). Because we dealt with large-scale data ($N = 24\,194$) in this study, choosing the model with the highest speed was important.

In this study, we used 10 classes of living-room objects, including *art walls, cabinets, ceiling lights, chairs, curtains, floor lamps, plants, rugs, sofas*, and *tables*. We trained the YOLOv3 model to recognize the objects in the 10 classes. By using YOLO Mark, we labeled 1899 living-room interior images to identify instances of 10 object classes. We trained the YOLOv3 model with data created by using the ground truth information of the bounding boxes. We extracted bounding box information from the objects detected in the image. Because most bounding boxes overlapped in 2D representations of 3D spaces, when the bounding boxes for different objects overlapped, we cropped and stored the overlapping part for accurate analysis (Fig. 2b-1). If the removed area was 75% or greater of the original size, we did not save the object.

To evaluate the performance of the YOLOv3 model trained on the 10 classes of living-room objects, we collected 100 images of living-room interiors that were not used during training. The images for the performance evaluation included 10 class objects. After labeling the ground truth of these images, a detection test was performed. Table 1 presents the precision and recall results for each object. The average precision of 10 object classes was 0.8773, and the average recall was 0.8380.

3.1.4. *Material recognition and segmentation*

We used the Materials in Context Database (MINC) dataset (Bell *et al.*, 2015) for material detection in interior images. MINC includes a larger amount of data in 23 material categories when compared to other material databases and is sampled with greater variety. Bell *et al.* (2015) used DL to recognize the material in images and segment them into 23 material regions. They used MINC to train CNN models and produced an efficient convolutional framework by including a conditional random field connected to a trained CNN classifier. Bell *et al.* (2015) attempted different methods to classify materials across a full scene; we used the method with the highest accuracy among various classification methods. The best single model used was GoogLeNet without average pooling. The accuracy of the model taken by Bell *et al.* (2015) was 70.4% in the mean class and 78.8% in total.

Figure 5b shows the 23 material classes used in the full-scene material classification. They also divided the 23 material classes into a comprehensive range, as shown in Fig. 5b. In this work, a material image of the same size as the original image was stored in our living-room interior images using the material recognition and segmentation method (Fig. 2c). The stored material image was divided into 23 colors indicating areas showing different materials (Fig. 5).

3.1.5. *Color extraction*

We used the representative color characteristics of objects extracted from the interior images to perform an efficient analysis. Because we used interior images of living rooms in Korea, we used

Figure 5: Material recognition and segmentation result. (a) Raw image and result image and (b) color by material area.

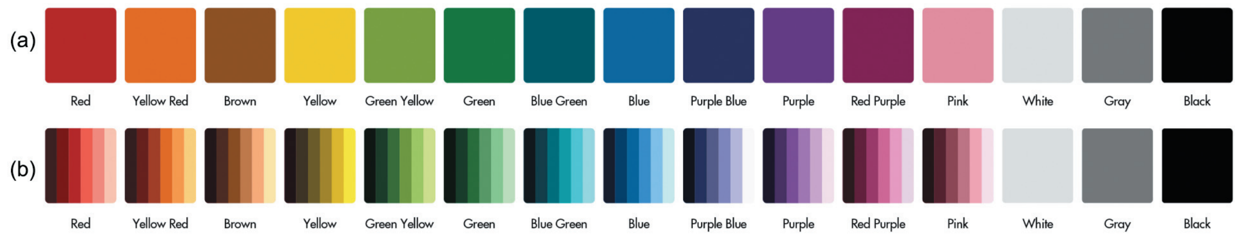

Figure 6: The extracted color was divided into a range through KS color. (a) Basic 15 color palette and (b) 75 colors palette divided by brightness (L∗).

Korean Standard (KS) colors (Korean Agency for Technology and Standards, n.d.) to classify the representative categories. KS color has been studied in terms of those used in Korea for efficient use. Figure 6 shows the KS colors, which include 15 basic colors, of which 12 are chromatic and three are achromatic. We created a color palette by using KS colors, as shown in Fig. 6a.

The visual significance of the design elements is essential for style analysis (Hyun *et al.*, 2015). We considered human vision for visual significance when analyzing interior design style images. Therefore, we selected the CIELAB color space, which can be expressed most closely to the color perceived by human vision. Unlike the commonly used RGB or CMYK colors, CIELAB has a uniform color distribution because its CIELAB color space was defined based on research on human vision (Robertson, 1977; Harold, 2001). Therefore, colors are invariant to differences in display equipment or printed media. Additionally, the color difference expressed in the CIELAB color space is similar to that seen by human vision.

We used the colorgram Python library to perform color extraction on material images extracted from objects. We extracted up to 50 colors from each object image by using colorgram as the RGB values and color ratios. Then, we converted the extracted RGB colors into CIELAB colors for use. We calculated the RGB values for the CIE1976L∗a∗b∗ conversion process according to the existing literature (Patruno *et al.*, 2019; Anami *et al.*, 2020; Kim *et al.*, 2017). The CIELAB color space is a short form of CIE1976L∗a∗b∗ (Robertson, 1977). We expressed the colors coordinated in CIELAB as L∗, a∗, and b∗, in which L∗ denotes brightness, a∗ is the degree of red and green, and b∗ is the degree of yellow and blue. For a more accurate color matching, we subdivided colors according to their L∗ values, representing the brightness of the color among the L∗a∗b∗ values of the KS color, as shown in Fig. 6b. In this way, except for black, white, and gray—which we had divided according to the L∗ value—we subdivided the remaining 12 colors into six and composed a palette consisting of 75 colors, as shown in Fig. 6b.

Finally, color matching was performed to determine the color extracted using the color palette. In the color-matching process, the color distance (ΔE) between the color palette and detected color was calculated and then matched to the color in the palette with the minimum ΔE. The color distance (ΔE) was calculated using the CIEDE2000 method (Sharma *et al.*, 2005). Sharma *et al.* (2005) modified the CIEDE2000 calculation method by considering a perceptual uniformity problem of the human eye. Sharma *et al.*'s CIEDE2000 E calculation method was based on two colors $\{L^*_i, a^*_i, b^*_i\}_{i=2}$ and the parametric weighting factors (k_L, k_C, and k_H) of the color's lightness, chroma, and hue. The calculation method is as follows (Equation 1).

$$\Delta E_{00}\left(L_1^*, a_1^*, b_1^*;\ L_2^*, a_2^*, b_2^*\right) = \Delta E_{00}^{12} = \Delta E_{00}. \tag{1}$$

3.2. Network analysis

3.2.1. *Data structure and projection*

In this paper, we present an expanded version of the data structure and data analysis framework as first introduced in prior research (Park *et al.*, 2021). In contrast to the previous study, we used a data structure with added furnishing materials and supplemented the framework for analyzing the furnishing relationship. We extracted data on colors and materials of furnishings from living-room images of eight interior styles. We used data projection to analyze the relationships between the extracted data. Data projection is essential for formulating an intuitive data structure for large-scale data ($N = 24\,194$) to be fast and accurate. As a result, we projected the extracted data onto color, material, and furnishing networks.

We created an intuitive data structure by using a single representative color and material. Specifically, we used representative colors and materials of furnishing to set up the data projection direction to reveal the relationships between furnishings and the principles of color and material pairings in interior images. Rather than use the detailed properties of furnishings, we used the color and material with the highest ratio as representative features to analyze the color and material data. We regarded that using colors and materials with the highest proportions as representative features is an intuitive method.

Figure 7 shows that the data matrix for each furnishing that we extracted contained the color ratio in the column and material ratio in the row. Notice in Fig. 7 that a *sofa* with white color and leather material in 0.72 and 0.8, respectively, occupies the highest ratio in the object. According to our framework, the sofa in Fig. 7a was named *White-leather*-sofa. As a characteristic of furnishing, we used the value of the highest-ratio of "color" and "material" in furnishing. The furnishings of an interior image have three characteristics: one object class, one highest ratio color, and one highest-ratio material. We also projected a color–material-furnishing (MF) network onto color-furnishing (CF) and MF networks to analyze the relationship between color, material, and furnishing. Consequently, the furnishing of Fig. 7 was a *White-sofa* and, simultaneously, had the properties of a *leather-sofa*. For this reason, our data have a structure identical to that shown in Fig. 8a.

Each of the 10 object classes had different interior design characteristics. We divided the 10 object classes into four furnishing groups according to their degree of functionality and decoration, as shown in Fig. 9. As part of our investigation into how furnishing types influence interior design, we refined the data structure based on the furnishing group, as shown in Fig. 8b. Figure 8a-2 and b-2 show the sample data structure of an image in *Natural style*. Figure 8b-2 shows that the data structure is more subdivided according to the furnishing group compared to Fig. 8a-2.

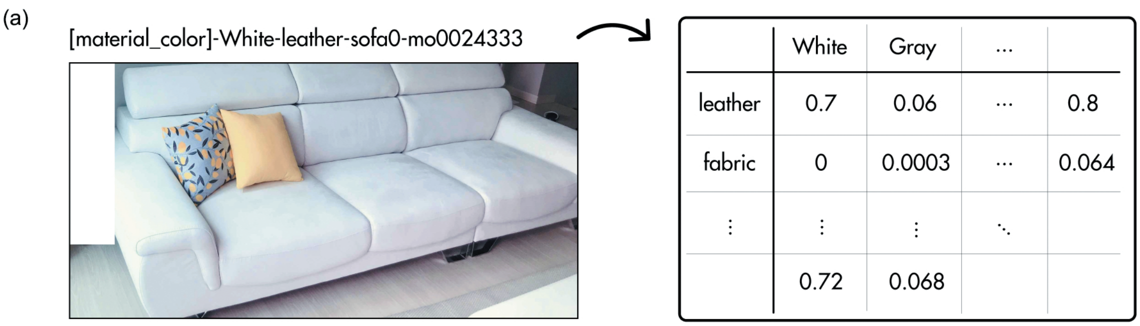

Figure 7: Example of color–MF image and data matrix.

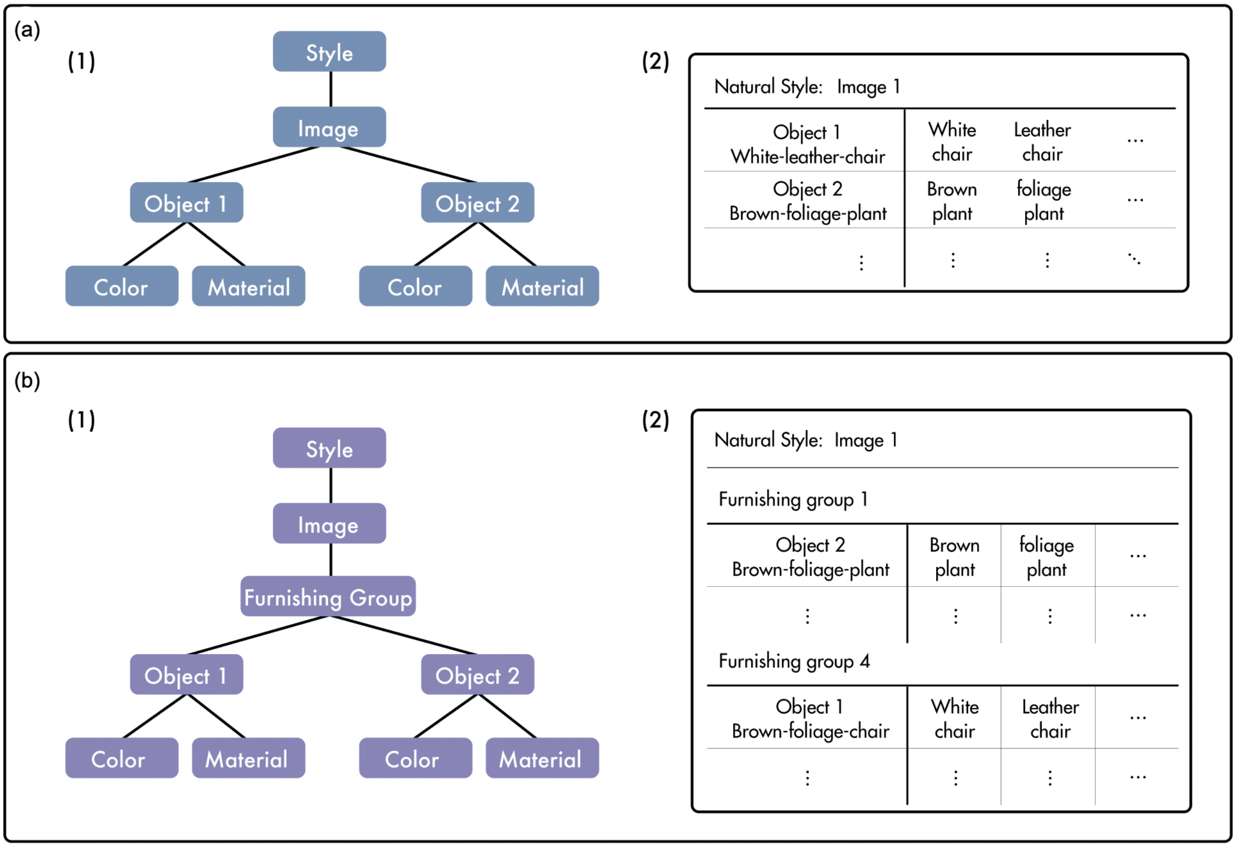

Figure 8: Data structure of the interior image in eight styles. (a) Whole data structure and data example and (b) group data structure and data example.

Figure 9: Ten object classes divided into four furnishing groups.

3.2.2. *Prevalence and authenticity, authentic image scoring*

We composed a dataset of 150 types of CF and 230 types of MF to analyze the effect of single and pairing CF and MF on interior style. It consists of 15 colors, 23 materials, and 10 furnishing units. By using the authenticity algorithm (Ahn *et al.*, 2011), we calculated the proportion (prevalence) of furnishing in each style and the relative prevalence (authenticity) of furnishing compared with the other styles. A high prevalence value indicates that furnishing (or furnishing pairing) is used frequently in an interior style, and a high authenticity value indicates that it is relatively influential compared to other interior styles.

The interior style of the object was s, furnishing was i, total number of images per style was N_s, total number of images containing i by style s was n_i^s, and prevalence of furnishing in the image was P_i^s. Equation (2) provides the formula for prevalence. Equation (3) provides the formula for authenticity, where $< P_i^{s'} >_{s' \neq s}$ is the average prevalence of other styles, excluding the corresponding style. The authenticity algorithm proposed by Ahn *et al.* (2011) is as follows:

$$P_i^s = n_i^s / N_s \tag{2}$$

$$A_i^s = P_i^s - < P_i^{s'} >_{s' \neq s} \tag{3}$$

The prevalence and authenticity of furnishing pairs and triplets were calculated to find meaningful pairings for each style. The pairs and triplets were calculated as the total number ($n = 2, 3$) of overlapping combinations for each object (${}_nH_2, {}_nH_3$, respectively). The calculation method was the same as above, and the formulas were given in Equations (4) and (5).

$$P_{ij}^s = n_{ij}^s / N_s;\ P_{ijk}^s = n_{ijk}^s / N_s \tag{4}$$

$$A_{ij}^s = P_{ij}^s - < P_{ij}^{s'} >_{s' \neq s};\ A_{ijk}^s = P_{ijk}^s - < P_{ijk}^{s'} >_{s' \neq s} \tag{5}$$

Using the above formula, to understand the effect of specific furnishing type on style, we calculated the single prevalence and authenticity for each of the 10 object classes and calculated the prevalence and authenticity of pairings (pair, triplet) within the same furnishing group. Because there were two furnishings in Groups 1, 2, and 3, the number of groups furnishing pairs and triplets was ${}_2H_2, {}_2H_3$. Group 4 contained four furnishings, and the number of Group 4 furnishing pairs and triplets in Group 4 was ${}_4H_2, {}_4H_3$.

We visualized the calculated authenticity values for comparison of the eight styles. We created an authenticity pyramid comprising the six highest authenticity values. The authenticity pyramid includes the authenticity values of the single furnishing, furnishing pairs, and furnishing triplets. With the authenticity pyramid, we can clearly see furnishings or furnishing pairings that style influences. We created an authenticity pyramid for each of the four furnishing groups to visualize the effect of the furnishing group on style.

We applied the calculated authenticity value for each furnishing group to the image to determine which image was most authentic in style. We performed authentic scoring for all furnishings detected in all types of living-room images. Authentic scoring was computed, including the single, pair, and triplet authenticity values of CF and MF for each group. Considering the difference in the number of objects detected in the image, we set all the scores as the mean authenticity score. When the image was i and the furnishing group was g, the sum of the authenticity scores of the furnishings belonging to group g in image i was s_g^i, and the number of furnishings in group g was n_g^i. In this case, the mean authenticity score of group g detected in image i was s_g^i / n_g^i and the mean authenticity score of images i was $S_i = \sum_{g=1}^{4} S_g^i / n_g^i$.

4. Implementation and Results

This section describes the results of analyzing the color and material data of furnishings extracted from eight interior style images. First, we analyzed the overall data trend by identifying the distribution of style, furnishing group, object class, color, and material data of interior images. Second, we investigated the pairing of significant CF and MF in each style using the authenticity algorithm. We calculated the authenticity values of CF and MF with two structures divided into the whole dataset and furnishing groups, generated the authenticity pyramid, and explained the detailed results.

4.1. Data overview

We collected 24 194 interior images of living rooms in eight styles. The number of images for each style was as follows. We included 7341 images in *Natural style*, 9540 in *Modern style*, 3083 in *Scandinavian style*, 1744 in *Vintage* style, 506 in *Unique styles*, 987 in *Classic_Antique style*, 655 in *Provence_Romantic style*, and 338 in *Korea_Asia style*. We analyzed the distribution trends of colors, materials, and furnishings data, and similar trends were observed for all styles (Fig. 10a and b).

In the color distribution, brown occupied a higher proportion, being included in approximately 28% of styles on average, followed by achromatic colors (the average proportion in each style was approximately 16% for *black*; 13% for *gray*; and 13% for *white*) (Fig. 10a). Compared to the colors, the distribution of materials tended to be relatively diversified, and the average for each style was 18% *painted*, 16% *fabric*, and 13% *wood*, in order of detection (Fig. 10b). Although the overall distribution was similar, there was a slight difference in the color or material for each style. For example, although *brown* had the highest proportion in all styles, *white* was second highest in *Scandinavian style*, and *black* was second highest in *Vintage style*. The number of object classes used in each style showed a similar tendency (Fig. 10c). Likewise, the object class had a slightly different ranking of proportions for each style. For example, in *Provence_Romantic style* and *Natural style*, the proportion of *plants* was high at approximately 23% each, and in *Korea_Asia style*, the *cabinet* was about 16%, which was relatively high compared to other styles (an average of about 11%). When the data were divided into four furnishing groups, Group 1 furnishings and Group 4 furnishings exhibited the highest distribution (Fig. 10d). The ratio of Group 1 was the largest in terms of Group furnishing number.

However, the color distribution for each object class showed a similar tendency in the distribution of each color by style within one object class; however, there was a difference in the detailed ratio for each style (Fig. 11). For example, when checking the color distribution graph of the *cabinet*, *black* and *brown* had the highest ratio of all styles. However, in the *Natural style*, *brown* occupied 52%, and *black* occupied 18%, whereas, in the *Classic_Antique style*, *brown* occupied 38% and *black* occupied 28% (Fig. 11a). Moreover, the distribution of material by 10 object classes showed a similar trend in the distribution by style as in color; however, the difference in the detailed ratio was smaller than that of color (Fig. 11). Additionally, the material distribution of the different object classes showed larger differences than the color distribution (Fig. 11).

These differences were affected by each furnishing group within the style. For example, in the *Scandinavian style* (Fig. 12a), which had the second highest *white* in the overall ratio, the ratio of *white* in all furnishings, except Group 4, was higher than that of other styles. This implied that in the *Scandinavian style*, *white* was more influenced by the detailed furnishing of Group 1–3 than by the functional furnishing of Group 4. In contrast, the material distribution differed in the furnishing group. Group 3 was *painted*, and Group 4 had the highest ratio of *wood* (Fig. 12b). This implied that each material had a similar tendency for each furnishing group. By studying the distribution of color and material by the entire style and object classes, we found that different furnishing types had different effects on the interior design process. Therefore, to derive the relationship between color and material, it was neces-

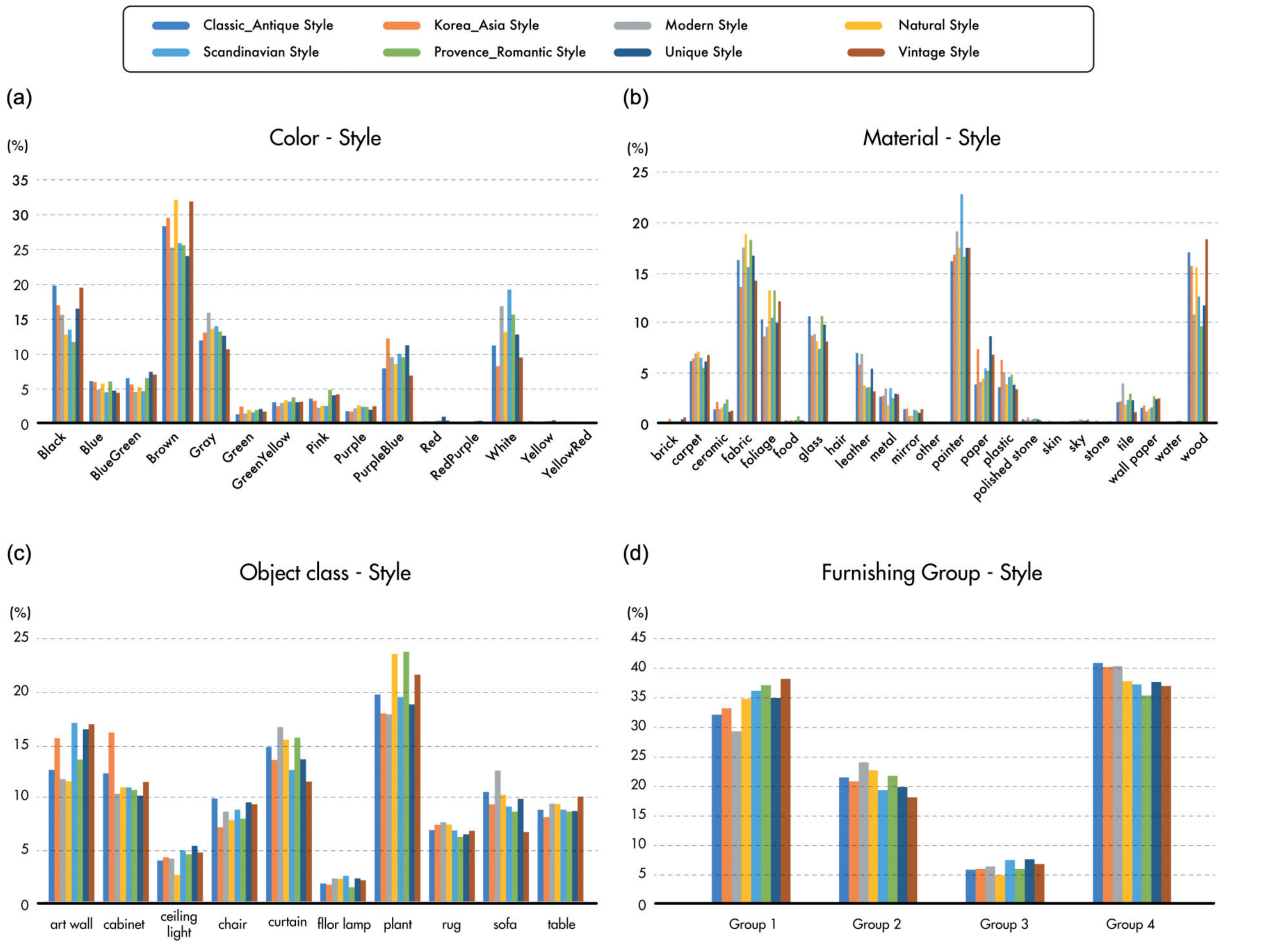

Figure 10: Distribution of color and material for eight styles. (a) The color distribution; (b) the material distribution; (c) the distribution of used object classes' number; and (d) the distribution of used number of furnishing groups.

sary to analyze the relative influence of color and material according to the furnishing group. Therefore, we conducted a detailed analysis as described in Section 4.2.

4.2. Results and discussion

4.2.1. *CF and MF authenticity pyramid by whole structure*

We used authenticity algorithms to analyze the relationships between furnishings in the extracted data. Notice the subtle differences in the data distribution for each style in Figs. 10, 11, and 12. In other words, detailed and intricate differences in design elements make differences between interior styles. The colors and materials that comprise a large proportion of the interior environment do not determine interior styles. Therefore, it is necessary to identify the distinctive characteristics of the relationship between color and material to define each interior style more specifically. We used an authenticity algorithm that can distinguish the influence of these subtle differences on interior style; we calculated the CF and MF authenticity and created authenticity pyramids. Authenticity pyramids consist of the six highest values for each authenticity type (single, pair, and triplet), as shown in Fig. 13. CF and MF authenticity pyramids exhibited different trends for each style.

The overall result of the CF and MF authenticity pyramids was consistent with the expert explanation. For example, according to Lee (2019a), in the *Natural style*, it was important to include natural items in the space; natural colors and materials with natural textures were used, such as wood, soil, and fabric. A similar color feeling was experienced throughout the interior, and the background color was mainly white. Our results showed that CF authenticity pyramid included many *brown* and *white* furnishings in *Natural style* compared to other styles (Fig. 13). A comparatively large number of *foliage*-furnishings were included in the MF authenticity types (single, pair, and triplet), and wood, fabric, and foliage were high in single furnishing (Fig. 13). Meanwhile, according to Lee (2019b), Scandinavia has geographical requirements involving short days and long winters, thus, creating a bright and comfortable atmosphere was the key in *Scandinavian* interior design. Therefore, the *Scandinavian style* created a warm atmosphere with fabrics and used white or light colors for most furnishings as well as wallpapers. The CF and MF authenticity pyramids in *Scandinavian style* included more *white*-furnishing and *painted*-furnishings than the other styles (Fig. 13). *Fabric*-furnishing was included in single and pair pairings (Fig. 13).

4.2.2. *CF and MF authenticity pyramid by furnishing group structure*

We found single furnishings and furnishing pairings that influenced each style through the CF and MF authenticity pyramids. Many elements were influenced by the furnishing type; all the results tended to be biased toward Group 4 furnishings for most singles and Group 1 furnishings for pairings. Additionally, the experts' description of the interior style considered the interior as a

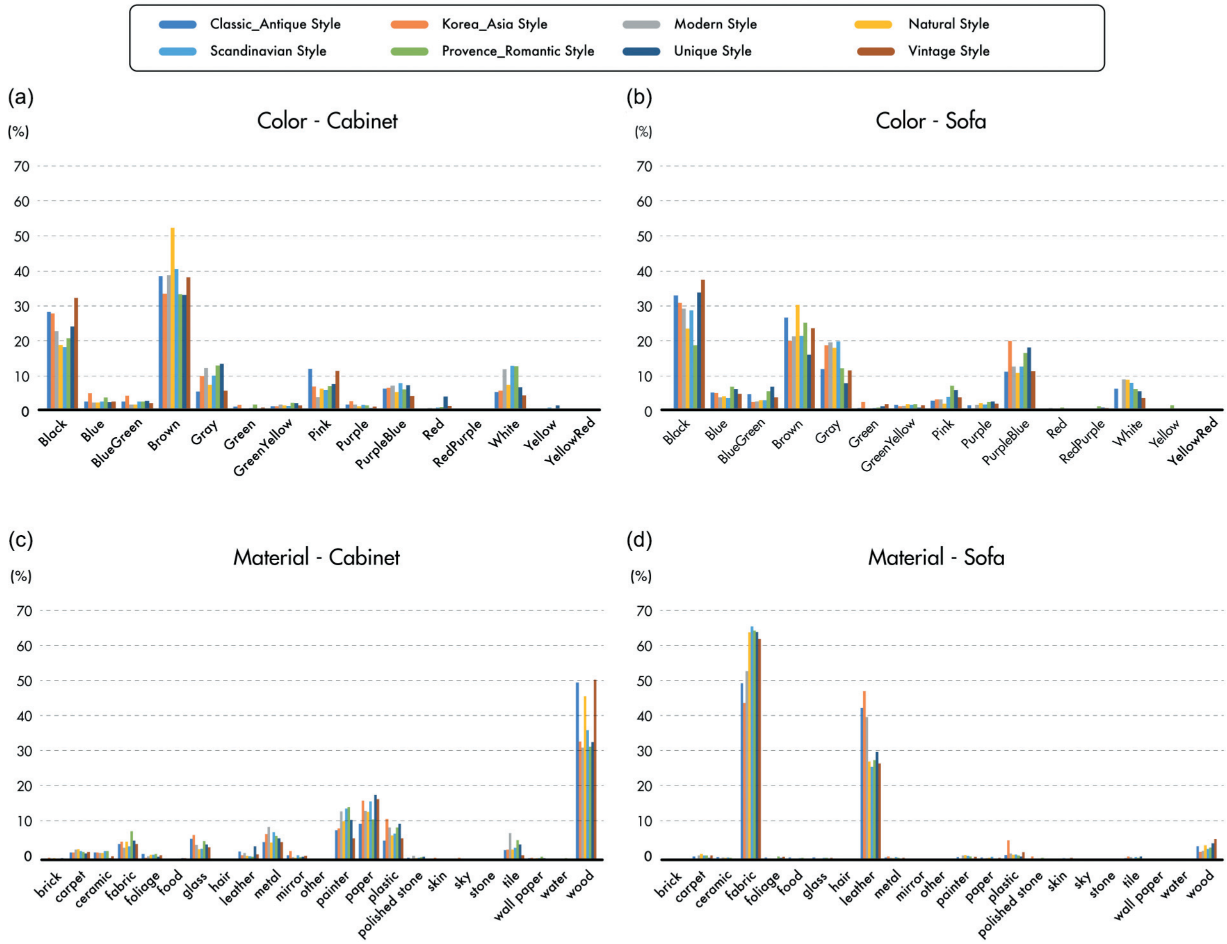

Figure 11: Data result of eight styles of 10 object classes. (a) The color distribution of the *cabinet*; (b) the color distribution of *sofa*; (c) the material distribution of *cabinet*; and (d) the material distribution of *sofa* (please note that only some of the 10 object classes have been attached.)

whole, and detailed information was lacking such as specific color or material of furnishings.

Therefore, detailed guidelines for furnishings were required without regard to the number of object classes in the interior design process. Thus, we identified items with a high influence on style for each furnishing type and conducted a detailed analysis. Therefore, considering furnishing types, CF and MF authenticity were calculated and eight styles of CF and MF authenticity pyramids were generated for each of four furnishing groups (Figs. 14 and 15). The single authenticity of 10 object classes consisted of the top three, and the pairing (pair, triplet) consisted of the top six. We compared and analyzed each style's CF and MF authenticity pyramids based on four furnishing groups.

The overall results followed the results of the whole CF and MF authenticity pyramids in all styles; however, the detailed effects on the furnishing group tended to be slightly different for each style (Figs. 14 and 15). Compared to other furnishing groups, Group 1 in each style differed in the highest furnishing pairings. For example, the pairing of *plants* prevailed in *Natural style* (Fig. 14). The pairing of Group 4 usually included *brown* and achromatic colors and *wood*. From this, we inferred that the functional furnishings of Group 4 used universal furnishing pairings consisting of colors and materials frequently utilized in all styles. Additionally, some styles used similar materials overall; however, the difference in color for each furnishing group represented a difference in style (Figs. 14 and 15). For example, *Natural style* and *Vintage style* did not differ significantly in their MF authenticity pyramids (Figs. 14b and 15b); however, in their CF authenticity pyramid, *Natural style* used a brighter color (Fig. 14a) than *Vintage style* in all furnishing groups (Fig. 15a). Finally, we found that color created an overall difference in style.

4.2.3. *Authentic style image scoring*

The nine images with the highest score using the proposed authentic style image scoring method showed distinct differences for each style (Fig. 16). For example, in Fig. 16a, the top nine *Natural style* images consisted of *brown* furnishings of Group 4 and *white* and *gray* furnishings of Groups 2 and 3. Compared to other styles, *foliage-plants* were noticeably included. In Group 4, the proportion of *fabric* and *wood-furnishing* pairings was high. However, the top nine *Vintage style* images contained many *black* and *brown* furnishings in all furnishing groups (Fig. 16b). Additionally, there were images in which some *foliage-plants* were included, although less than in the *Natural style*. Groups 2 and 4 included many *fabric*, *wood*, *carpet*, and *leather* furnishings, and most of Group 4 comprised *wood* furnishings. These results were equivalent to the expert's style descriptions and authentic style image scoring described above, suggesting colors and materials used in furnishing groups. Additionally, in the top nine images of each style (Fig. 16), the resulting image of our proposed authentic style image scoring method selected images that sufficiently reflected the results of the authenticity pyramid for each furnishing group.

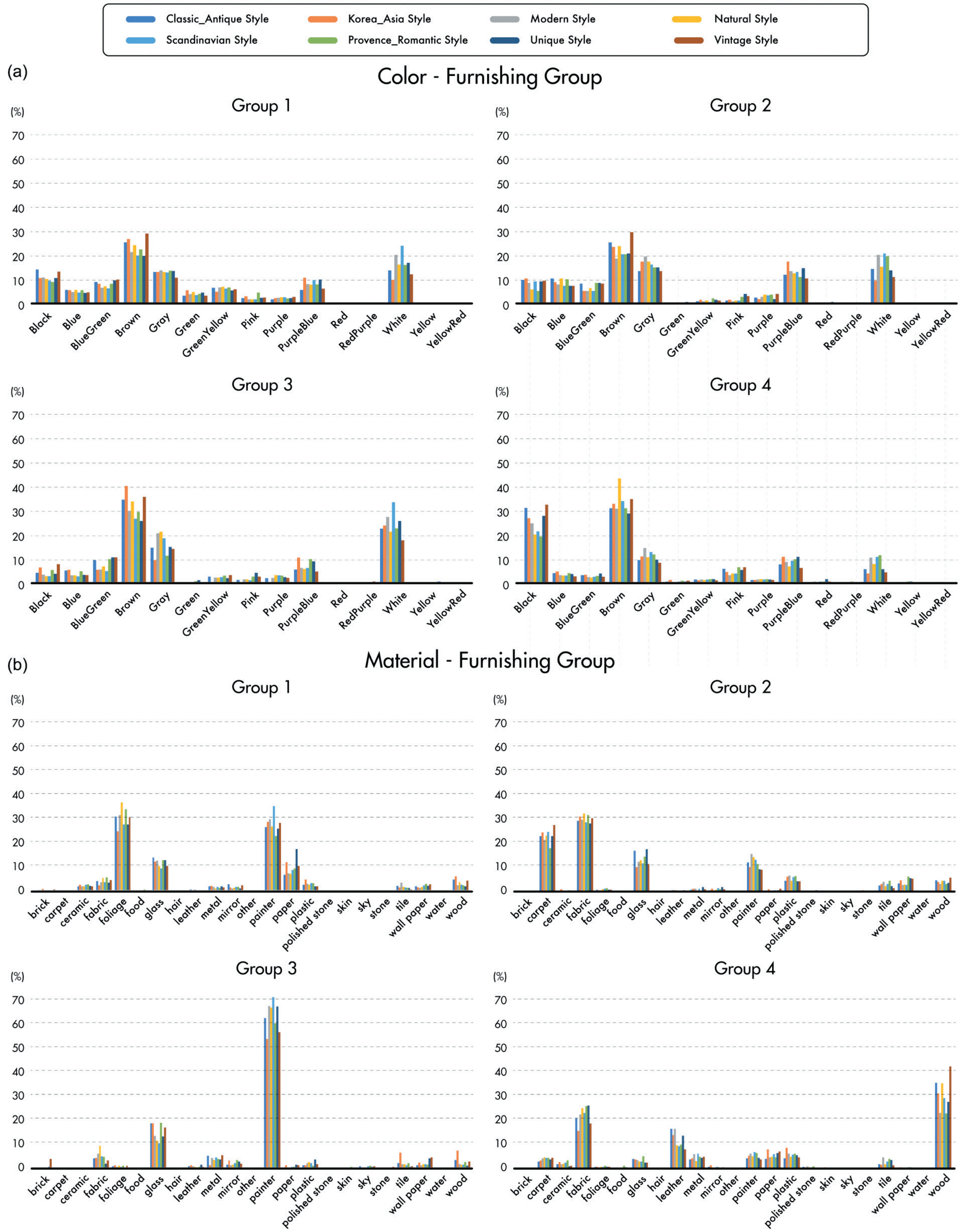

Figure 12: Distribution of eight styles in four furnishing groups. (a) Color distribution in furnishing group and (b) material distribution in furnishing group.

4.2.4. *Authentic style image scoring validation*

We compared the *mean* authenticity score (the method used to verify the validity of authentic style image scoring) with the *raw* authenticity score, calculated as a sum. The *raw* authenticity score showed results that were biased toward the furnishing type, with many detections in the image. For example, several images include *plant* furnishings with many detections. When we compared the top nine *Natural style* images by using *mean* authenticity scoring (see Fig. 17a) and *raw* authenticity scoring (see Fig. 17c),

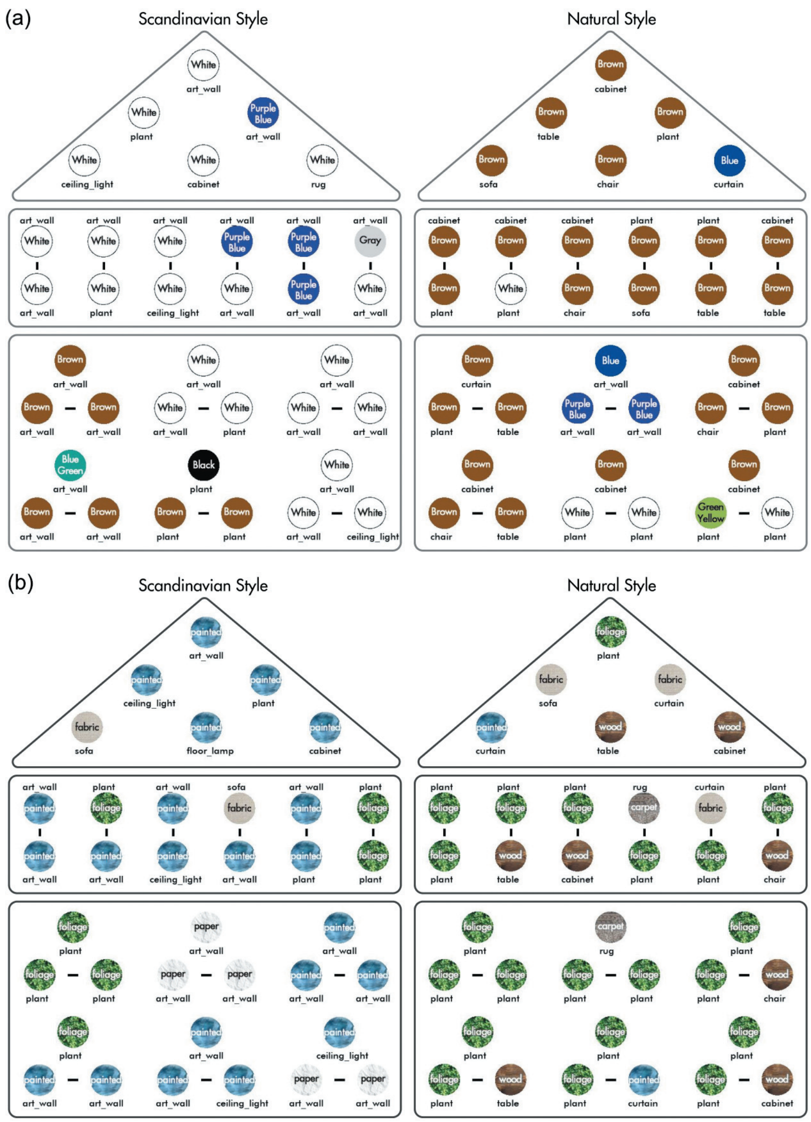

Figure 13: CF and MF authenticity pyramid for whole. (a) CF authenticity pyramid and (b) MF authenticity pyramid.

the image that uses the raw authenticity score contained excessive *plants*, making it difficult to show a general living-room interior (see Fig. 17c).

Additionally, each of the top nine images had a marked difference for each style, based on the *mean* authenticity score (in Fig. 17a and b). The top nine images with the most authentic *Natural style* (in Fig. 17a) used *brown-wood* furnishings. However, the lower nine images (in Fig. 17b) did not use *brown-wood* furnishing and contained many *white* or *black* furnishings overall. We tagged the lower nine images (in Fig. 17b) with *Natural style*; however, compared to the authentic top nine images, they showed a relatively *Modern style*. Additionally, in the image using the *mean* authenticity score (in Fig. 17a and b), the top and low images are significantly different; however, the image that uses the *raw* authenticity score (in Fig. 17c and d) had almost no difference between the top and low images. These results support our method of using the *mean* authenticity score to identify authentic images for each style.

Thus, most styles showed a significant difference between the scores of the top nine images and low nine images, and the top and low images each tended to be similar. However, some styles had a relatively inconsistent low nine images, as shown in Fig. 17f. While the low nine images of *Natural style* (in Fig. 17b) showed a unified image, the low image of *Provence_Romantic style* showed relatively inconsistent interior images (in Fig. 17f). The style of the interior image extracted from Today's House follows the user tag method. Therefore, we understood that because of the character of the data of Today's House, the style was tagged without the user clearly understanding it. Therefore, when inconsistent interior style images of *Provence_Romantic style* category were used, we had difficulties extracting authentic images. We found that in the *Natural style* used by many people, the users' understanding of the style was high, whereas, in the *Provence_Romantic style*, the understanding of the style was relatively low.

4.2.5. *Interior design implications and application*

Interior style information is not unified because it relies on the experience of experts to identify styles in the interior design process. We revealed universal pairing principles by quantitatively analyzing interior design styles using large-scale data, opening the possibility of using such data in interior design process.

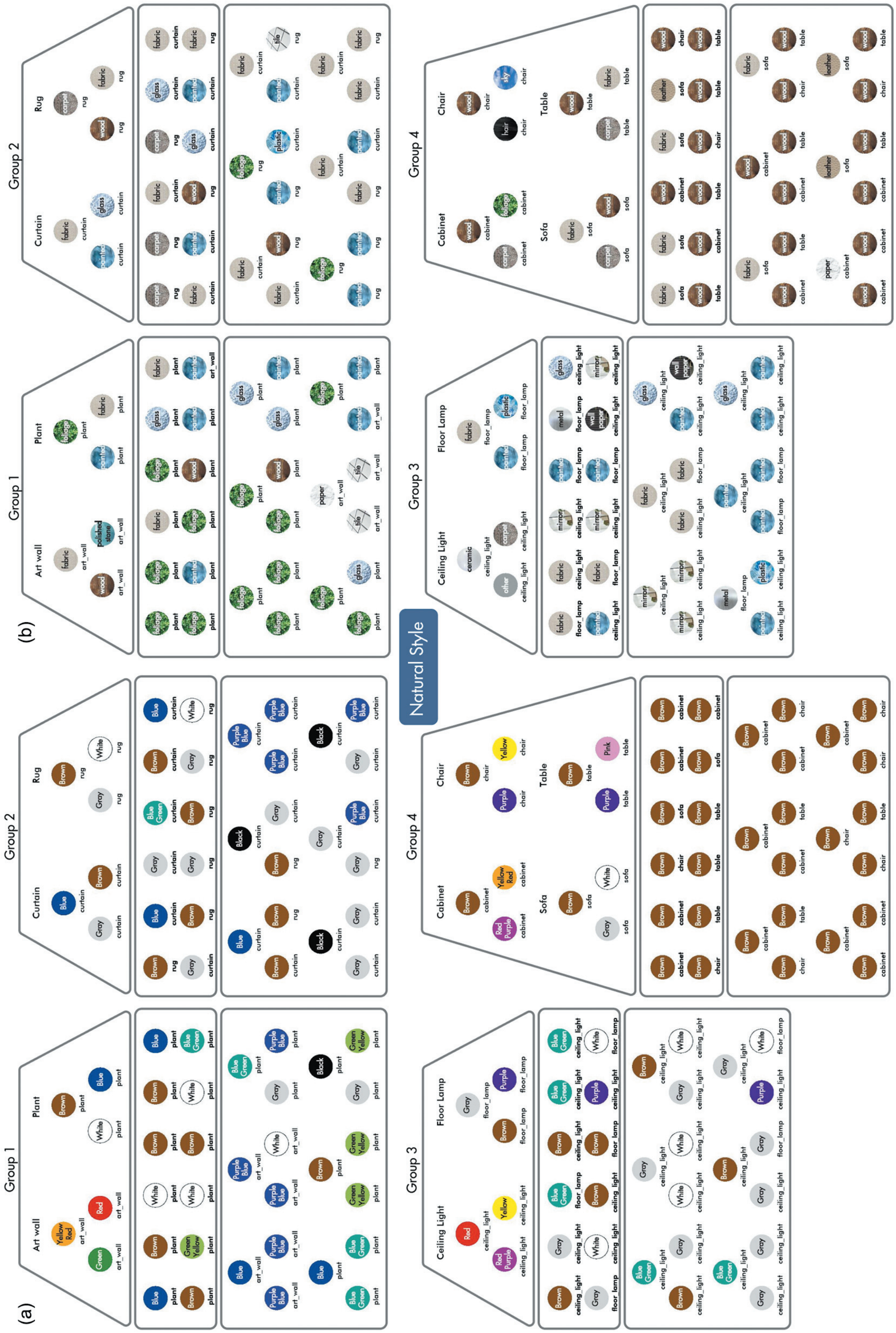

Figure 14: CF and MF authenticity pyramid by furnishing group. (a) CF authenticity pyramid in *Natural style* and (b) MF authenticity pyramid in *Natural style*.

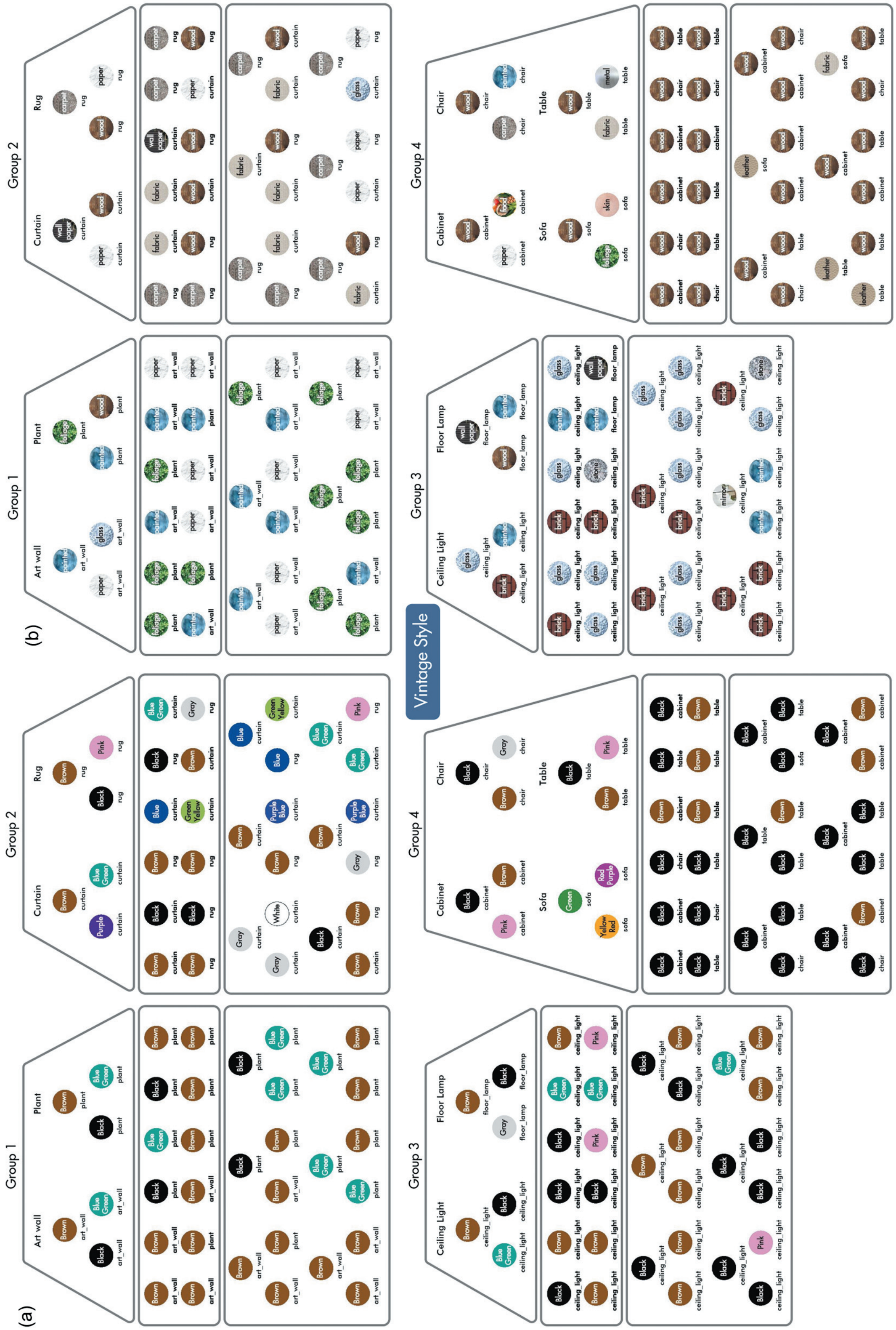

Figure 15: CF and MF authenticity pyramid by furnishing group. (a) CF authenticity pyramid in *Vintage style* and (b) MF authenticity pyramid in *Vintage style*.

Figure 16: (a) *Natural style* authenticity score top nine images (*mean* authenticity score). (b) *Vintage style* authenticity score top nine images (*mean* authenticity score).

First, the color and material pairing principle can be used to recommend or retrieve furnishings for each style. As online stores become more active, understanding design style or furnishing pairings that space owners desire is essential in selecting interior furnishings. However, the criteria for selecting an interior furnishing appropriate for a given interior style were ambiguous. On various interior design online platforms (e.g., ikea.com and ohou.se/store), selecting furniture suitable for interior style is challenging because furnishings are classified by their own characteristics. However, we not only analyzed the interior style, but also the types of furnishings, so we could identify which pairings of color and material of furnishings were used in each furnishing group. If the proposed framework is used to support the selection of interior furnishings, space owners with less understanding of the interior design process can intuitively select furnishings appropriate to their desired style. For example, by adding style information to the furniture category of an interior design online platform, we can recommend single furnishings with high authenticity for each furnishing group. If a chair suitable for a *Natural style* is required, with furnishing corresponding to wood, a brown chair with a high authenticity value can be retrieved. Alternatively, in the search process, the space owners can input the desired interior style and information on their furnishings. Then, various pairings optimized for style can be provided based on that data.

Second, by using the authentic images for each style we extracted, we are able to create a reference for the interior images and support it as a dataset for the retrieval system. The initial stages of interior design typically involve searching for numerous reference images. Therefore, it was essential to reproduce the interior designs in 2D. Additionally, it was relatively difficult to find an image suitable for desired style simultaneously during this process. However, using our eight styles of authentic images can help space owners find desired style images. For example, Karras *et al.* (2020) proposed a method to automatically generate images through StyleGAN. By applying their method, interior images can be automatically generated for each style through the images resulting from our framework. The existing generation method creates images using random features shown in the images. Additionally, we can synthesize images for each style on a parametric basis in terms of authenticity scores. Also, the proposed framework enables user to consider their desired design elements. Hence, our framework can accommodate much more specific conditions than existing interior image synthesis methods. We can use these synthesized images as interior style reference images. Additionally, we expect to be able to propose an interior reference image search system that can support the interior design process by applying authentic and synthesized images as a dataset to existing search system algorithms. In this case, our dataset can provide interior styles of more suitable quality. As a specific method, we can utilize the design support system of Son and Hyun (2022). They proposed an interactive system designed to support design retrieval and generation in the design process and provide feedback. By applying our dataset to their system, it can be used to support the interior design process in selecting furnishings appropriate to the desired style. Floor-plan reference images can be replaced with authentic interior images using our framework. The relationship between furniture in the interior image can also be analyzed by substituting information such as the connectivity and number of rooms into the furnishing. Also, Anandh *et al.* (2016) proposed an image retrieval system based on color, texture, and shape features. By applying our authentic images, the proposed framework can support space owners in searching for interior images that match their desired style. In addition, although the visual query-based search proposed by the existing system uses the overall characteristics of images, it can also support a more detailed search based on the relationship between furnishings and their authenticity value in the interior images.

5. Conclusions

In this study, we identified pairing principles of furnishing inherent in style in the interior design area, which was difficult to explain quantitatively with prior methods. The contributions of our study are summarized as follows.

To facilitate an understanding of the interior design process, we propose a novel data-driven framework to describe interior design by quantitatively analyzing large-scale interior design image data. Specifically, we derived the single and pairing principles of CF and MF that can influence interior styles by using the authenticity algorithm. We then calculated authentic style image scores to find authentic images in all styles. We identified authentic images for each style, with the resulting images consistent with the expert's

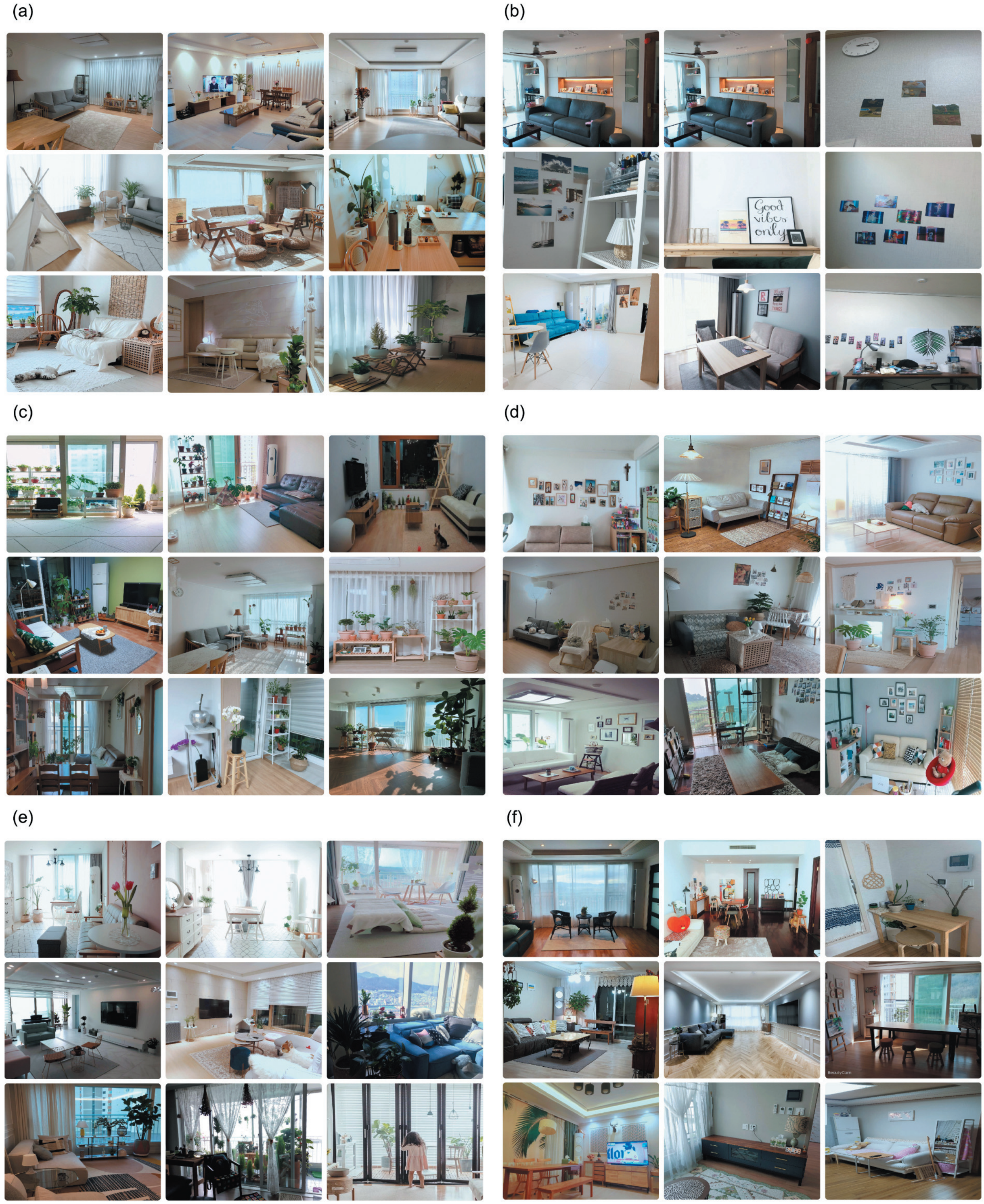

Figure 17: (a) *Natural style* authenticity score top nine images (*mean* authenticity score). (b) *Natural style* authenticity score low nine images (*mean* authenticity score). (c) *Natural style* authenticity score top nine images (*raw* authenticity score). (d) *Natural style* authenticity score low nine images (*raw* authenticity score). (e) *Provence_Romantic style* authenticity score top nine images (*mean* authenticity score). (f) *Provence_Romantic style* authenticity score low nine images (*mean* authenticity score).

style description. Furthermore, the analysis results supported the expert's explanations in terms of overall interior style and suggested specific furniture suitable for each style by furnishing type.

Our results from large-scale image data provided new evidence of the differences between several conventional interior styles. When we analyzed in terms of the furnishing group, the distribution of colors and materials for each style had differences, and we confirmed the detailed impact of each style through the authenticity algorithm. The findings suggest that *white* furnishings were used more often in furnishing groups containing more decorative than functional Group 4 furnishings. As these results show, we found pairings of detailed furnishings constituting different interior styles. Authentic image results for each style elicited through our framework showed differences in understanding styles among users of Today's House.

However, this study had three limitations in this study. First, we collected and analyzed only the furnishing data extracted through object detection from interior images. We did not consider interior backgrounds such as wallpaper, floor, and ceiling in the analysis process. In future research, the interior background can be analyzed in the same method as in furnishing. By analyzing the relationship with furnishing by adding the interior background, expanding the scope of interior design analysis is possible to include both space and home furnishing, which are the two major components of the interior design process.

Second, it was difficult to determine the consistency of interior design quality in the images from Today's House because non-expert users uploaded most images. However, the authenticity values for each style indicated that non-expert users have a widespread understanding of the interior styles. Therefore, we concluded that non-experts thoroughly conducted interior design process based on their knowledge of interior styles. In this respect, we can use user-reaction metadata, such as the number of likes and comments on a post (including images) to determine the quality of the interior design dataset in future work. Additionally, we can compare the combination of furnishings in interior design between expert and non-expert designs to identify the effects of various interior design references on non-experts.

Third, color, material, and finishing (CMF) express the unique characteristics of a product's design (Ugale & Thakur, 2021), and the importance of CMF is emphasized, as the main task is material and finish selection in the field of interior design and interior architecture (Becerra, 2016). In line with this importance, we can also analyze the finishing data in future studies. For example, by extracting glossy and roughness values from the MF image, incorporating finishing information into the color–MF network is possible. Analyzing furnishings, CMF will provide an opportunity to understand interior design more deeply.

The design process inevitably entails a decision-making process of choosing from the desired alternatives. Prior studies have explored various methods to aid decision-making in the design process (Zboinska, 2019; Chang *et al.*, 2020). Likewise, our novel framework opens up opportunities to aid decision-making and, in particular, can support the interior design process. Despite these limitations, we expect that the findings of this study will serve as a basis for furnishing design retrieval methods that can support the interior design process. We also expect this to enable the automatic generation of furnishing pairings as a more efficient design process in the future.

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Conflict of interest statement

None declared.

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