Enhancing the Interior Design Process with Crowdsourced Furnishing Pairing Recommendations

Semin Jin[1], Kyung Hoon Hyun[2*]

[1]Department of Interior Architecture Design, Master's Student, Hanyang University, Seoul, Korea

[2]Department of Interior Architecture Design, Associate Professor, Hanyang University, Seoul, Korea

Abstract

Background Focusing on the importance of style and color in interior design, the necessity of comprehending the attributes of design elements is emphasized. While previous research lacks explicit rules for furnishing pairing recommendations specific to interior design styles, our study aims to address this gap through dataset analysis and machine learning techniques. The goal is to enhance designer-consumer communication in the interior design process, facilitating better-informed design choices.

Methods Our methodology involved the analysis of a substantial dataset containing 24,184 living room images sourced from Today's House, an online home furnishing platform. We integrated data reflecting crowd preferences and applied machine learning for object detection and color extraction, converting visual information into quantifiable data. Additionally, we customized association rule mining to reflect crowd preferences, aiming to generate furnishing pairing rules specific to various interior design styles. We validated the effectiveness and practicality of these rules and our methods through expert interviews.

Results The generated rules were organized based on three criteria: Adjusted-Support, Adjusted-Confidence, and Adjusted-Lift. We presented results that scored higher in these metrics, accompanied by illustrative image cases. These rules, having been validated through interviews with design experts, aid customers in making informed decisions and enhance designer-consumer communication and collaboration.

Conclusions Our research presents a novel framework that enriches the interior design process through data-driven insights. The study's contributions are threefold. First, we develop an Adjusted Association Rule Mining method for interior-style analysis and furnishing recommendations. Second, we demonstrate how different metrics like Adjusted-Support, Adjusted-Lift, and Adjusted-Confidence can be used to interpret and apply furnishing pairing rules effectively. Third, expert interviews confirm the utility of the rules in enhancing consumer decision-making and facilitating a more collaborative design process. We emphasize the importance of adaptable and predictive analytical methods in interior design and potentially other recommendation-based fields.

Keywords Furnishing Paring, Data-driven Design, Adjusted Association Rule, Interior Design

This work was supported by National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIT; RS-2023-00208542), and supported by the research fund of Hanyang University(HY-202300000003633)

*Corresponding author: Kyung Hoon Hyun (hoonhello@hanyang.ac.kr)

Citation: Jin, S., & Hyun, K. H. (2024). Enhancing the Interior Design Process with Crowdsourced Furnishing Pairing Recommendations. *Archives of Design Research, 37*(2), 79-101.

http://dx.doi.org/10.15187/adr.2024.05.37.2.79

Received : Jan. 31. 2024 ; **Reviewed :** Mar. 17. 2024 ; **Accepted :** Apr. 21. 2024
pISSN 1226-8046 **eISSN** 2288-2987

1. Introduction

Online home-furnishing platforms (e.g., IKEA, houzz.com, and ohou.se) have become integral to the global interior design market by meeting diverse consumer needs with real-life design inspirations from both professionals and individuals. Beyond shopping, they foster community engagement and reflect current market trends, enhancing accessibility to practical and visually appealing designs. Within these platforms, systems for recommending products that account for users' preferences are essential, aiding in the exploration of extensive choices. However, the concept of "style" in interior design is subjective and multifaceted, making it challenging to quantify for systematic search or recommendation purposes. Moreover, selecting furnishings requires considering various factors (e.g., types, colors, materials, styles), which add complexity to the recommendation process.

Considering these challenges, extensive research and system development has focused on combining interior design elements. For example, these studies enable the search or recommendation of visually or stylistically similar products regardless of the product category (Liu et al., 2017, August; Liu et al., 2015; Pan et al., 2017, December; Tautkute et al., 2017, September; Wang et al., 2018), and support searching for products similar to those selected in interior images (Shiau et al., 2020, August), or assist in selecting in consideration of the context with surrounding spaces (Sreedhar et al., 2022, October). However, there are few studies that explicitly present furnishing pairings, nor are there any that explore the need for practical assistance for designers and consumers in real-world applications. Bridging this gap, the aim is to collect and quantify data from Today's House, a leading online platform in South Korea, to generate furnishing pairing rules. These rules, grounded in authentic user-generated content, address the practical, real-world application of style furnishing pairing recommendations. According to Lee et al., 2021,May, consumers evince a significant trust in realistic data, such as shared photos and reviews, as reliable references, emphasizing the importance of practical, real-world applications of style analyses.

To consider the various types of information and combinations of interior design elements in our research, we built style-specific data from interior images. Given the critical impact of color elements on the design process and occupants' emotions (Cha et al., 2020; Poldma, 2009), our approach prioritizes style and color elements in furnishing selection. Therefore, we collected living room images from Today's House, extracting color information from 10 representative living-room-furnishing objects and background elements for use as furnishing data. Additionally, we utilized user response data, specifically the number of scraps, to measure crowd preferences. Scrap is one of the interactive features on the Today's House platform, a positive mark from users for images they save to view later. This approach not only considers the visual aspects of design elements but also incorporates the crowd's preferences, enabling the generation of practical pairing rules. Consequently, we explored methods for applying these rules to an actual recommendation system. We conducted in-depth interviews with expert designers to investigate the implications of these rules and to explore how they influence designers, consumers, and corporate strategies. The following four main tasks were conducted to achieve these goals:

1. A vast set of Korean living room styling images (N = 24,184) and crowd preference data was collected from Today's House.
2. Objects and dominant colors were extracted from the images and converted into structured interior-style data. Dominant colors were extracted from 10 furnishing objects and background elements.
3. The adjusted association rule mining method was employed to analyze the interior furnishing elements and crowd preference data, focusing on generating style-specific rules and exploring their integration into a recommendation system to understand the interrelationships among the interior design elements.
4. These rules were then validated through in-depth interviews with expert designers, discussing their practical utility for designers, consumers, and corporate strategies.

2. Related Research

2. 1. Quantifying Design Style

"Styling" in design refers to a creative problem-solving process in which designers express solutions in distinctive forms. This process is more than an artistic expression; it serves strategic functions that significantly influence product development and brand identity. Therefore, styling is a consistent process of making decisions regarding form, function, and technology, reflecting the designer's unique approach (Person et al., 2016; Wisetchat and Stevens, 2018). Thus, research on the quantification and evaluation of styles has been emphasized for several reasons. First, analyzing style provides a means of assessing creativity within designs. According to Chan (2001), measuring and defining style aids in understanding the flow of creativity and style changes across all art and design fields, including interior design. Style evolves, and analyzing these changes and characteristics can serve as a vital tool for evaluating an individual designer's creativity. Second, designers leverage "style" to substantiate the effectiveness and reasoning of their designs to clients or users. Industrially, styling transcends individual creativity and contributes to a product's market position and brand identity (Person et al., 2016). This significance has led to studies on strategic style development. For example, in automobile design research, Hyun and Lee (2018) proposed a strategy for designing a novel shape that aligns with a company's brand identity while also fitting market trends. Similarly, Jeon et al. (2021) proposed a system that supports design direction by combining brand style, trend style, and the designer's individual style in the field of fashion design. A common method for quantifying style is to analyze it as a design element, as seen in the studies (Graces et al., 2014; Hyun and Lee, 2018; Kadner et al., 2021; Ostrosi et al., 2019). In a broader context, Chan (2001) suggested that style evaluation is effective when similarities among design elements are assessed, a principle applicable across the artistic and design domains. Domain-specific studies include the following. Garces et al. (2014) developed a method for distinguishing styles in detailed illustrations by simultaneously comparing various attributes, including color, contrast, texture, and stroke. Hyun and Lee (2018) and Ostrosi et al. (2019) evaluated car design styles using a set of characteristic lines on the exterior of a car. Kadner et al. (2021) expressed a font style in three-dimensional (3D) space by combining typographic elements, such as ratio, serif, and thickness. The prevalent theme in these studies is that a design's distinctiveness becomes apparent through repeated and common elements, intensifying style recognition. Similarly, Chan (2001) highlighted the importance of syntax in style recognition, noting that the properties of the design element unit and the combinations and relationships of design elements must be considered in the overall design context. In line with these insights, we aim to quantify interior styles. Instead of merely cataloging the design elements indicative of various interior styles, we sought to establish pairing rules specific to each style and explore their applicability.

2. 2. Analyzing Furnishing and Pairing

Previous studies analyzing interior styles have defined and analyzed design elements based on the specific objectives and methodologies of the research. For instance, Hasirci and Ultav (2020) evaluated the styles of architectural structures in specific eras by assessing their interiors and furniture, focusing on the forms, materials, and functions gathered from floor plans and sketches. These studies offer an in-depth understanding of the styles and their corresponding designs. Regarding quantitative research, efforts have focused on identifying common features within interior styles or clustering design characteristics that are crucial for precise style recognition. For example, Tautkute et al. (2019) and Yaguchi et al. (2022) classified interior style images by comparing features such as the color, finishing, and function of interior design elements. Yaguchi et al. (2022) advanced this by proposing a style classification method using color histograms and text description data, thereby detecting interior styles using textual, color, and object detection information. Tautkute et al. (2019) introduced a system that comprehends style similarities through text descriptions of interior images, thereby facilitating the search for stylistically compatible furniture.

Despite their effectiveness in style classification, these methodologies do not explicitly demonstrate the relational characteristics of design elements for each style. Therefore, we aim to identify the design elements and combinations frequently appearing in each style to develop guidelines for interior design element selection. Our approach is aligned with Park and Hyun (2022)'s methodology for analyzing design elements across various interior styles. They utilized object detection, color, and material information to identify meaningful furnishing combinations and distributions within a style, particularly in comparison with other styles. However, we aim to discover pairing rules within the data of a single style, prioritizing the discovery of applicable design patterns over a generalized classification of styles.

2. 3. Furnishing Pairing and Recommendation Methods

The process of selecting furnishings in interior design is complex and requires considerations ranging from furniture type, design, and style to size, and cost. For designers, this task is particularly demanding because they must accommodate the preferences and requirements of their clients, which require access to extensive information (Yoon et al, 2010). Selecting interior furnishings is not done in isolation but requires a harmonious pairing with the surrounding space, necessitating systems that support product exploration within this context. To support interior color selection (Gue et al., 2023) allow users to check various scene views of an interior 3D model using eye-tracking.

Style-compatible furnishing combinations in interior design has been the subject of a number of studies. For instance, Liu et al. (2017, August) emphasized including category (e.g., bed, sofa, chair, and table) and style attributes (e.g., modern, classic, and natural) in recommendation systems to reflect user's visual preferences. Additionally, studies have assessed the harmonies between styles by comparing furniture across categories (Liu et al., 2012; Pan et al., 2017, December; Wang et al., 2018). Liu et al. (2012) and Pan et al. (2017, December) proposed a model that measures the style compatibility, not the geometrical similarity, of object classes to assess the harmony between different types of furniture. Wang et al. (2018) presented a synthesis method for measuring the style compatibility of furniture and arranged a combination of furniture with a matching style in a space in the format of a 3D image. These studies have focused on furniture selection and not on all interior elements. Consequently, this neglects the relationship between furnishings and background elements, which constitute a relatively large proportion of interior design. Thus, this study focuses on the categorization of interior design styles and the pairing of furnishings appropriate for each style.

Moreover, other studies and systems have been developed to assist in the pairing and recommending interior products during purchase situations. For instance, the "Shop the Look" system assists users in finding products similar to those in interior design images (Shiau et al., 2020, August). The "Search with Space" system employs augmented reality, allowing users to place products in their space virtually to check for compatibility with the existing environment (Sreedhar et al, 2022, October). Consequently, systems supporting the selection of furnishings in interior design should operate from a pairing perspective that considers harmony with the surrounding context. However, despite these advancements, limited in-depth studies exist on how users utilize these systems and the type of support they receive during furniture selection. This gap indicates the need for further research in this field, not only for designers but also for consumers.

To aids the selection of furnishings in interior design, we established style-specific pairing rules by employing a mining technique known as association rule mining (ARM). Introduced by Agrawal et al. (1993), ARM operates on the principle of identifying frequently recurring patterns, specifically those that surpass a predefined threshold value. First, it allows for evaluating the types and distribution of interior design elements based on their occurrence frequency. Second, it reveals significant combinatorial relationships among the design elements. The rules derived from ARM are articulated as {a set of items} → {item}, embodying an "If–Then" relationship. This relationship is instrumental in forecasting new data, and even with a single dataset, it is possible to uncover association rules with high predictive power (Luna et al., 2019). Third, a great advantage of ARM is its flexibility and applicability. This methodology is not confined to a specific type of data. For instance, it can be used to analyze product review data in e-commerce using text data (Awad and Mahmoud, 2021) and to analyze influential users based on user information from social media (Iqbal et al., 2022). Moreover, we utilized an ARM variant known as Adjusted Association Rule Mining (AARM), which accommodates subjective factors such as price, profits, and user feedback, adapting to the specifics of the application context (Hikmawati et al., 2022; Nguyen et al., 2019). This adaptability renders it suitable across various domains, including interior design. Further details on the AARM methodology are provided in the Methods section.

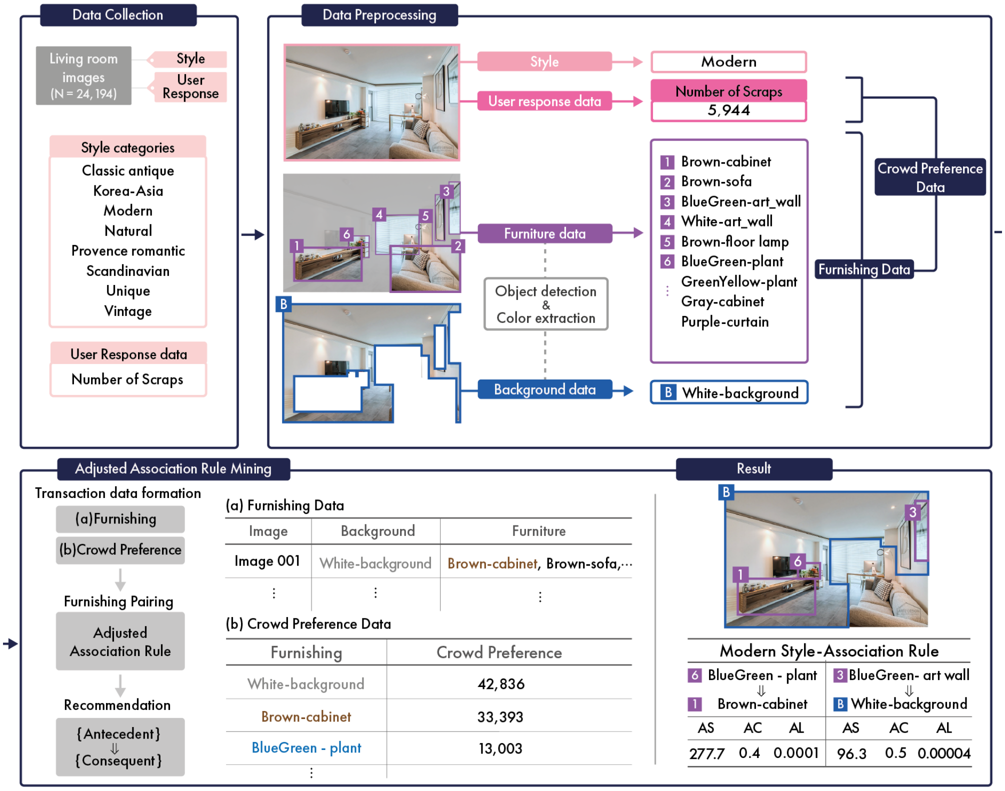


Figure 1 Furnishing Pairing Recommendation Framework

3. Method

The methods used in this study were divided into two stages (as illustrated in Fig. 1). First, Korean living room image data were uploaded into eight style categories on Today's House, and user response data were collected. The data-driven framework proposed by Park and Hyun (2022) was utilized to extract the design elements and color attributes from the living room images at the furnishing level. Second, using furnishing and crowd preference data, the furnishing pairing rule for interior design elements was identified using AARM. A method was presented for calculating the AARM, and interpretation methods were applied to an interior-style analysis.

Although our research is anchored in the framework of (Park and Huyn 2022), it has several distinct and critical attributes. First, it integrates crowd preference data into the analysis through a comprehensive approach that considers both design aesthetics and user preference. Second, our study introduces a distinct advantage in the rule-generation method, which allows the formulation of style-specific rules using only data pertinent to a single style. This approach not only simplifies the process but also significantly eases future data updates and expansion. In contrast, Park and Hyun's method, which involves relative analysis, requires navigating through the entire dataset to discern style-specific pairings and their influences. Consequently, this potentially complicates the process of data adaptation and extension. Finally, we incorporated structural elements as background data to ensure that comprehensive interior information was included in the analysis.

3. 1. Data Collection and Processing

3. 1. 1. Data

Two main types of data were collected. First, we collected living room images (N = 24,194) from Today's House, spanning uploads from April 2014 to July 2020. Professional styling images were also included; however, considering that they included actual styling images of general semi-professional users, they are more realistic and practical. While they encompass professional styling, their value is accentuated by the realism and practicality stemming from semi-professional users' actual styling images. This is because consumers often rely on such data as practical and trustworthy references (Lee et al., 2021, May). Today's House segments interior styles into eight types: Classic Antique, Korea-Asia, Modern, Natural, Provence Romantic, Scandinavian, Unique, and Vintage styles. The style information provided by the individual uploading the content was utilized as a label in our study. The number of images collected for each style is listed in Table 3. Second, we collected user response data assigned to the image. Owing to the community-like character of the Today's House platform, we could aggregate additional data on the number of visitors, likes, scraps, shares, and comments; scrap data were used as crowd preference data for AARM methods in this study. The act of scrapping images indicates the user's intent to revisit certain designs, arguably positioning it as the most affirmative user response data. This is supported by the active use of Today's House features, such as the scrapbook, allowing users to save images for later reference. Therefore, in the context of our study, scrap data can be considered an important response reflecting crowd preferences. We compiled the scrap data until July 2020, starting from the initial upload period of the images (April 2014 to July 2020). Table 3 details the cumulative numbers of scraps garnered from Today's House.

These data are valuable because they reflect real-life experiences and preferences of the general public, offering insights that are readily applicable and relatable. Although they may include individual user data that lack consistency or professionalism, they offer broad insights into consumer demand and preferences. Consequently, this research will play a crucial role in fostering understanding and communication among designers, companies, and the public. Additionally, this dataset, which reflects the crowd's preferences, contributes to enhancing the accuracy and reliability of the research. The data structures and their sizes are listed in Fig. 2.

Figure 2 Data Structure

3. 1. 2. Object Detection and Color Extraction

For a precise analysis of the interior design, we identified and quantified design elements by detecting furnishing objects and background elements in the images and subsequently extracting and quantifying their color information. While we employed the framework introduced by Park and Hyun (2022) to identify design elements, we exclusively used color information. This strategic focus was selected for several reasons. First, color is crucial in interior design, significantly influencing the overall ambiance and aesthetic representation of a space. It sets the scene and mood of the interior and often guides further design choices. Second, incorporating various interior design elements (such as texture, material, or specific design features) would complicate the analysis due to a significant increase in potential scenarios. By focusing solely on color information, we simplified our rule extraction process, making it more practical and effective. Thus, our research prioritizes color information not only for the feasibility of rule generation but also for its substantial impact on the comprehensive interpretation and experience of interior spaces.

Object detection. We employed the You Only Look Once (YOLO) v3 model (Redmon and Farhadi, 2018) to identify ten types of living room furnishings from interior images and to extract their dominant colors. The detected items included sofas, tables, cabinets, chairs, ceiling lights, floor lamps, curtains, rugs, plants, and art-wall, which are representative of living room spaces. Additionally, we analyzed the backgrounds of these images, considering them as integral design elements. These backgrounds, comprising structural components like floors, walls, and ceilings, were present in every image, contributing one piece of "background" data per image.

Color Extraction. Following object detection, the Colorgram Python library was utilized to derive the colors of the detected furnishing objects and background. We employed fifteen standard colors from the Korean Standard color palette: Red, YellowRed, Yellow, GreenYellow, Green, BlueGreen, Blue, PurpleBlue, Purple, RedPurple, Brown, Pink, White, Gray, and Black. For each detected object and background element, we calculated the color covering the largest area within its bounding box. The predominant RGB values were mapped to these 15 colors, thereby simplifying the information for efficient rule creation. To enhance the accuracy of color extraction and account for variations in lighting conditions, a white balance correction was applied to all images prior to analysis.

3. 2. Adjusted Association Rule Mining

Association Rule Mining (ARM) relies on the basic principle of identifying correlations among data elements and forming rules based on their frequency of co-occurrence (Agrawal et al., 1993). A key advantage of ARM is its straightforward data structure, which facilitates the discovery of correlations between style-specific furniture combinations without necessitating complex machine-learning models. In this study, ARM was used to explore relationships among two or more furniture combinations in design cases, specifically within interior images.

Hikmawati et al. (2022) introduced a novel method to improve the traditional ARM approach by incorporating additional factors like price, profit, and availability into the analysis. Furthermore, traditional ARM methods typically require setting a minimum support parameter, but Hikmawati et al.'s approach adjusts the parameter values based on the data itself, eliminating the need for manual setting. This adaptive feature is a significant advantage, as detailed in Section 4.1, where parameters adjusted for each style can be reviewed. Consequently, we developed Adjusted Association Rule Mining (AARM) methods tailored for interior-furnishing pairing recommendations that consider crowd preferences in images.

3. 2. 1. Furnishing Data Transformation

In our study, we used two main types of data: furnishing data and crowd preference data from the Today's House platform. First, we extracted detailed information from each image and identified various types of furniture and their colors, revealing combinations and patterns in current designs. Simultaneously, we assessed the popularity of each image by counting how many times users have "scrapped" it, indicating designs they found appealing or inspiring. This approach allowed us to weigh the significance of each design element, giving more importance to those that the crowd frequently scrapped, thereby reflecting genuine public interest. The number of scraps assigned to each item was multiplied by its probability of occurrence in that style category. The crowd preference for furnishing item

A can be calculated using Eq. (1). Consequently, images with several scraps were more likely to be included in the rules. Fig. 3 illustrates the processing of these two types of data. By integrating these elements—the tangible pairing information from the images and user preferences—we conducted a comprehensive analysis that bridges the gap between theoretical design trends and practical, real-world appeal.

$$\textit{Number of Scraps (A)}=\textit{Number of Scraps(A)}\times P(A) \qquad (1)$$

(a) Furnishing Data

Image	Background	Furniture	Scraps
Image 001	White-background	Brown-cabinet, Brown-sofa, ···	5,944
Image 002	White-background	Black-sofa, Blue-art wall, ···	1,696
Image 003	Brown-background	Black-sofa, White-chair, ···	1,032
⋮	⋮	⋮	⋮

Furnishing	Number of Scraps (A)
White-background	5,944 + 1,696 + ··· = 42,836
Brown-cabinet	5,944 + ··· = 33,393
Blue-art wall	1,696 + ··· = 13,003
⋮	⋮

(b) Crowd Preference (White-background) = Number of Scraps (White-background) x P(White-background)

Figure 3 Example of Furnishing Data Transformation

3. 2. 2. Adjusted Association Rule Calculation

In this study, we used the AARM methodology. Although it maintains the principles of standard ARM metrics, it incorporates adjustments based on crowd preferences. Table 1 below summarizes the key components of this method.

Table 1 Association Rule Mining Metrics

Metric	Definition	Formula
Support	Measures the frequency of A and B occurring together.	Support (A, B) = P (A∩B)
Confidence	Indicates the probability of finding B given A's presence.	Confidence (A, B) = P (A∩B) / P (A) = Support (A, B) / Support (A)
Lift	Evaluates the strength of the association between A and B, compared to their random co-occurrence.	Lift (A, B) = = P (A∩B) /P (A) x P (B) = Confidence (A, B) / Support (B)

Table 2 summarizes the key components of AARM metrics. Adjusted Support (AS) quantifies the frequency of furniture combinations, adjusted to reflect the crowd preferences for the furniture pieces in the images. The AS reflecting the crowd preference increases the frequency of furniture appearing in images with numerous scraps. When a style furnishing pairing rule scores high on the AS index, it suggests that the combination is not only common but also popular with crowd users.

Table 2 Adjusted Association Rule Metrics

Metric	Definition	Formula
AS	Frequency of A and B, weighted by crowd preference.	AS (A, B) = P (A∩B) x Crowd Preference [a] (A, B)
AC	Predictive power of A's presence on B, considering crowd preference.	AC (A, B) = AS (A, B) / AS (A)
AL	Influence of A on B's occurrence, relative to B's standalone presence, considering crowd preference.	AL (A, B) = AC (A, B) / AS (B)

[a] Crowd Preference(A,B) = (Crowd Preference(A) + Crowd Preference (B)) / 2

Adjusted Confidence (AC) is the ratio of A to B found in the design examples, including A. The conditional probability indicates how often B appears based on an image containing A. Thus, it indicates confidence in furniture combinations. This shows the general pattern of item combinations in a styling image. Adjusted Lift (AL) is the ratio of combinations A and B within the B combination standard and represents the robustness of the rules. The AC of each combination was divided by the frequency of combination B. A high AL value indicates that an item's appearance positively impacts the appearance of B, such that the larger the lift value, the more substantial the impact of the rule on the co-occurrence of items A and B (Hikmawati et al., 2022).

4. Adjusted Association Rule Results

4. 1. Data Overview

A total of 24,184 images were analyzed using the AARM, and the numbers of collected images and extracted rules for each style are listed in Table 3. Hikmawati et al. (2022) proposed a method for obtaining minimum support in adaptive rule models. The traditional ARM methodologies do not prescribe a standard way to define minimum support value. Thus, we adopted the same strategy as Hikmawati et al. (2022), who divided the average AS per item by the number of images to determine minimum support. In this section, we organized the association rules in the AARM based on three criteria: AS, AC, and AL. We examined every rule across styles and reported the results, focusing on rules with higher values in each metric, accompanied by illustrative image cases.

Table 3 Number of collected images and extracted rules

Metric	Classic Antique	Korea–Asia	Modern	Natural
Number of images	982	338	9,538	7,340
Number of rules	391	54	1,245	1,751
Minimum support	0.25	0.08	0.68	0.093
	Provence Romantic	Scandinavian	Unique	Vintage
Number of images	655	3,081	506	1,744
Number of rules	220	1,155	158	586
Minimum support	0.006	0.16	0.08	0.17

4. 2. Rule Generation with Adjusted Support

The rule with AS focuses on furnishing combinations frequently found in images preferred by the crowd. This method multiplies the probability of antecedent and consequent items appearing together by the value of crowd preference, thereby weighting the frequency of furnishing combinations. Notably, AS (A, B) and AS(B, A) are identical; thus, the AS value does not reflect the directionality between items. Our analysis highlights the types of furniture most seen and appreciated by the crowd in each style, specifically within the top 10% of AS rules (N = 567). These included Classic Antique (N = 39), Korea-Asia (N = 5), Modern (N = 125), Natural (N = 175), Provence Romantic (N = 22), Scandinavian (N = 116), Unique (N = 16), and Vintage (N = 59). As a result of analyzing the top 10% AS rules by style, Brown-background, Brown-cabinet, Brown-plant, Brown-table, and Brown-chairs were included in the top AS rules in all styles. The Today's House data analysis shows that brown-colored furniture is commonly used in living room interiors in South Korea and can be seen as an item that is highly connected to other furniture. Therefore, these types of brown furniture can be interpreted as essential items compatible with all styles. As illustrated in Fig. 4, certain rules were consistent across multiple styles. For example, the pairing of {Brown-cabinet} → {Brown-background}, {Brown-plant} → {Brown-background}, and {White-art wall} → {White-background} had high AS values in common in all styles. South Korean living room interiors often use these combinations as basic item combinations.

(a) Classic Antique Style

No.	Rule	AS
1	Brown-art wall ⇒ Brown-background	387.3
2	Brown-plant ⇒ Brown-background	381.1
3	Brown-cabinet ⇒ Brown-background	377.2
4	Brown-sofa ⇒ Brown-background	325.2
5	Brown-sofa ⇒ Brown-background	324.8

(b) Korea-Asia Style

No.	Rule	AS
1	Brown-background ⇒ Brown-table	187.9
2	Brown-table ⇒ Brown-background	187.9
3	Brown-plant ⇒ Brown-background	138.9
4	Brown-chair ⇒ Brown-background	134.1
5	Brown-cabinet ⇒ Brown-background	87.9

(c) Modern Style

No.	Rule	AS
1	Brown-cabinet ⇒ Brown-background	2760.9
2	Black-sofa ⇒ Brown-background	2493.3
3	White-art wall ⇒ White-background	2394.8
4	Brown-plant ⇒ Brown-background	2312.8
5	White-plant ⇒ White-background	2212.3

(d) Natural Style

No.	Rule	AS
1	Brown-background ⇒ Brown-plant	5295.8
2	Brown-plant ⇒ Brown-background	5295.8
3	Brown-cabinet ⇒ Brown-background	5186.5
4	Brown-table ⇒ Brown-background	3916.3
5	Brown-plant ⇒ Brown-cabinet	3022.0

(e) Provence romantic Style

No.	Rule	AS
1	Brown-background ⇒ Brown-plant	351.8
2	White-background ⇒ Brown-plant	113.5
3	White-background ⇒ White-plant	106.2
4	Brown-background, Brown-cabinet ⇒ Brown-plant	90.5
5	Brown-background, Brown-table ⇒ Brown-plant	72.4

(f) Scandinavian Style

No.	Rule	AS
1	White-art wall ⇒ White-background	3290.2
2	White-background ⇒ White-art wall	3290.2
3	White-plant ⇒ White-background	2453.2
4	White-background ⇒ White-plant	2453.2
5	Brown-cabinet ⇒ Brown-background	1951.7

(g) Unique Style

No.	Rule	AS
1	Brown-plant ⇒ Brown-background	228.8
2	Brown-art wall ⇒ Brown-background	225.4
3	Brown-cabinet ⇒ Brown-background	183.6
4	White-background ⇒ White-art wall	169.7
5	White-art wall ⇒ White-background	169.7

(h) Vintage Style

No.	Rule	AS
1	Brown-background ⇒ Brown-art wall	2575.0
2	Brown-art wall ⇒ Brown-background	2575.0
3	Brown-plant ⇒ Brown-background	2391.7
4	Brown-table ⇒ Brown-background	1650.0
5	Brown-cabinet ⇒ Brown-background	1584.6

Figure 4 Top 5 AS rules by style

In contrast, some furnishing pairings were exclusive to specific styles, as shown in Fig. 5. For instance, Pink-cabinet appeared in the Classic Antique style (Fig. 5a), Green-plant only in the Natural style (Fig. 5b), and White-floor lamp in the Scandinavian style (Fig. 5d). Similarly, Gray-cabinet, Gray-table, and Gray-chair were common in the Modern style (Fig. 5c), with White-themed items like White-ceiling light, White-table, White-cabinet, White-chair, White-sofa, and White-rug dominating in both Modern (Fig. 5c) and Scandinavian styles (Fig. 5d). These unique elements are easily recognizable as characteristics of their respective styles. Therefore, furnishings pairings specific to a particular style can be regarded as descriptive rules for that style. However, despite these unique associations, no significant differences existed in AS rules among the styles. This observation confirms the commonality of certain furnishing pairings in Korean living room design.

(a) Classic Antique Style (N = 39)

No.	Rule	AS
29	Pink-cabinet ⇒ Brown-background	84.5

(a) Image examples of rule 29

(b) Natural Style (N = 175)

No.	Rule	AS
107	Green-plant ⇒ Brown-background	645.4
155	Green-plant ⇒ Brown-cabinet	508.5

(b) Image examples of rule 107 rule 155

(c) Modern Style (N = 125)

No.	Rule	AS
14	White-rug ⇒ White-background	1213.2
26	White-sofa ⇒ White-background	822.1
31	White-cbinet ⇒ White-background	771.1
43	White-chair ⇒ White-background	599.9
83	Gray-cabinet ⇒ Brown-background	402.5
88	Gray-table ⇒ Gray - background	394.4
124	Gray-chair ⇒ White-background	330.4

(d) Scandinavian Style (N = 116)

No.	Rule	AS
20	White-rug ⇒ White-background	846.5
35	White-cabinet ⇒ White-background	673.0
88	White-sofa ⇒ White-background	417.0
100	White-chair ⇒ White-background	401.5
102	White-floor lamp ⇒ White-art wall	397.8
105	White-floor lamp ⇒ White-background	396.4

(c) Image examples of rule 83

(c) Image examples of rule 88

(c) Image examples of rule 124

(d) Image examples of rule 102

(d) Image examples of rule 105

Figure 5 Among the AS top 10%, furnishing combinations only appear in each style

4. 3. Rule Generation with Adjusted Confidence

A rule with AC has the direction of Antecedent → Consequent and is expressed as { a set of antecedent items } → { a single consequent item }. After ranking the association rules extracted from each style by their AC, we analyzed the furnishing combinations and reported the top 30 rules. The AC measures the confidence of the furnishing pairing, representing the ratio of instances where A and B coexist among design cases including A. This metric helps pinpoint highly dependable furnishing pairings unique to each style. In sorting by AC, backgrounds feature prominently across most styles. These rules suggest a standard practice in which designers first select furniture for the interior plan before settling on a background. This sequence is evident in the rules and has practical application value in the design process. Fig. SA presents the representative furnishing pairing rules for each style.

In the Modern style (Fig. SA3), Brown-background mainly appeared. The furnishings that precede this consequence were primarily Blue-Green or Blue furniture, fabrics, lighting, and decorative objects. In the Scandinavian style (Fig. SA6), Blue furniture appeared on Brown-background, and Brown-background dominated in the Vintage style (Fig. SA8). Owing to the rule's Unique style (Fig. SA7), Brown-background is extracted from most rules.

(a) Classic Antique Style

No.	Rule			AC
1	Blue-rug	⇒	Brown-background	175.4
2	Blue-sofa	⇒	Brown-background	14.1
6	Blue-chair	⇒	Brown-background	9.5

(a) Image examples of rule 1

(a) Image examples of rule 2

(a) Image examples of rule 6

(b) Natural Style

No.	Rule			AC
3	Blue-rug	⇒	Brown-background	16.4
8	Blue-sofa	⇒	Brown-background	11.4
11	Blue-chair	⇒	Brown-background	8.2

(b) Image examples of rule 107

(b) Image examples of rule 107

(b) Image examples of rule 107

Figure 6 Example of AC of (a) Classic Antique Style and (b) Natural Style

In the Provence Romantic style (Fig. SA5), Pink-cabinet and art wall were paired with Brown-background. The color that appeared due to the Korea-Asia style was Brown and mostly comprised a background (Fig. SA2). In the Classic Antique style (Fig. SA1), Brown-background was extracted from the consequences of 24 rules among the top 30 rules. For example, Blue, BlueGreen, and PurpleBlue fabrics, furniture, lighting, and decorative objects were associated with Brown-background. In the Natural style (Fig. SA4), all consequences of the top 30 AC rules were extracted in Brown, and most were background data. A significant relationship was found between Blue furniture and Brown backgrounds. The combination of Blue or PurpleBlue furniture and Brown-Background was common in Classic Antique and Natural styles, as shown in Fig. 6.

Overall, Brown-background is an everyday item that is used repeatedly; therefore, it mostly appeared consequently. Furnishings connected to Brown backgrounds differed slightly from style to style. Analysis of rules with high AC values revealed that each style relied heavily on similar rules. Additionally, the differences between the styles significantly influenced the details. Comparing images and rules, for example, the Classic Antique style contained blue-colored furniture with high saturation. In contrast, large windows and sunlight caused bright-colored furniture to appear slightly blue in the natural style (Fig. 6).

4. 4. Rule Generation with Adjusted Lift

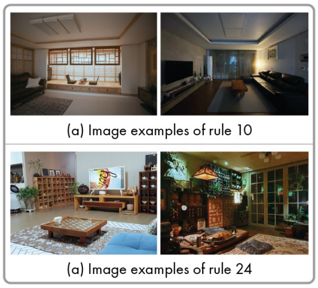
A rule with AL indicates the robustness of the combination rules. According to Hikmawati et al. (2022), prioritizing rules based on AL is useful. The higher the AL, the more potent the rule and, consequently, the more pronounced its correlation with the respective style. Rather than rules sorted by AC values, various furnishing items appear in rules with AL. Unlike rules with an AC, unique furnishing–pairing rules are available. Among these, a rule preceded by a background is often extracted, which is suitable for the newly designed living room. If the background information is fixed in the antecedent, the rules can help in selecting furniture that matches the background. Rules with clear patterns or matching the style described in the top 30 were emphasized. Fig. SB illustrates the top 30 furnishing pairing rules sorted by AL values.

(a) Korea_Asia Style

No.	Rule	AL
10	Black-sofa ⇒ Black-cabinet	0.0284
14	Black-sofa ⇒ Brown-cabinet	0.0179
16	Black-sofa ⇒ Brown-background	0.0137
20	Brown-curtain ⇒ Brown-plant	0.0082
22	Brown-curtain ⇒ Brown-background	0.0075
24	Brown-curtain ⇒ Brown-cabinet	0.0073

(b) Modern Style

No.	Rule	AL
4	Blue-rug ⇒ Brown-curtain	0.0013
13	Blue-rug ⇒ Brown-background	0.0009
16	Blue-rug ⇒ Brown-plant	0.0009
17	Blue-rug ⇒ Brown-cabinet	0.0008
22	Gray-floor lamp ⇒ Gray-sofa	0.0007
24	Gray-floor lamp ⇒ Gray-background	0.0006
26	Gray-floor lamp ⇒ Brown-background	0.0006



(a) Image examples of rule 10

(a) Image examples of rule 24

(b) Image examples of rule 4

(b) Image examples of rule 22

(b) Image examples of rule 13

(b) Image examples of rule 24

(c) Provence Romantic Style

No.	Rule	AL
1	White-background, ceiling lingt ⇒ White-chair	0.0351
7	Pink-art wall ⇒ Gray-art wall	0.0188
8	White-chair ⇒ White-table	0.0176
9	PurpleBlue-art wall ⇒ Brown-sofa	0.0123
12	PurpleBlue-art wall ⇒ Brown-art wall	0.0117
14	Pink-art wall ⇒ Brown-art wall	0.0104
21	PurpleBlue-art wall ⇒ Brown-cabinet	0.0080

(d) Vintage Style

No.	Rule	AL
5	PurpleBlue-rug ⇒ Black-plant	0.0014
7	PurpleBlue-rug ⇒ Brown-cabinet	0.0013
11	White- rug ⇒ White-background	0.0012
14	Black-rug ⇒ Black-sofa	0.0011
23	Black-rug ⇒ Black-plant	0.0009
28	Gray-rug ⇒ Gray-background	0.0008
29	PurpleBlue-rug ⇒ Brown-background	0.0008

(c) Image examples of rule 1

(c) Image examples of rule 9

(d) Image examples of rule 11

(d) Image examples of rule 7

(d) Image examples of rule 14

(d) Image examples of rule 29

Figure 7 Example of AL of (a) Korea_Asia Style, (b) Modern Style, (c) Provence Romantic Style, (d) Vintage Style

For example, design cases using BlueGreen-art wall in Classic Antique were often used together with Black-cabinet, Black-table, Black-chair, Brown-chair, Brown-art wall, or BlueGreen-curtain (Fig. SB1). When using Black-rug, Black-sofa or Black-table of the same color also tended to appear together. As for the Vintage style (Fig. SB8), achromatic rugs were highly correlated with achromatic backgrounds, sofas, and plants. PurpleBlue-Rug was also connected to a Black-plant and Brown-cabinet. Rugs in Vintage style paired well with achromatic furniture, objects, and backgrounds. In the Natural style (Fig. SB4), Blue-rug was connected to Brown-curtain, cabinet, background, and plant, and Black-rug links Black-table, sofa, chair, and cabinet. In addition, the Blue-sofa appears along with Brown-chair, table, plant, and background, and the Blue-table followed the Brown-chair, background, and cabinet. As for the rules of the Natural style, Brown items followed blue furniture. In the Provence Romantic style (Fig. SB5), Pink and Purple blue-art wall appeared with Gray and Brown art wall or Brown sofa and cabinet.

A White rug matched well with a White cabinet, an art wall, and a curtain in the same color. Among the upper rules of the Scandinavian style (Fig. SB6), many combinations were preceded by the background. Blue backgrounds matched Brown furniture, whereas Black backgrounds matched furniture of the same color. The Modern style tended to have many rules that preceded the background. These rules assist in the selection of furniture after designing the background. In addition, Blue-rug was connected to Brown-curtain, background, plant, and cabinet (Fig. SB3), and if Gray-floor lamp preceded it, Gray-sofa, curtain, and background were likely to appear together. In the Korea-Asia style (Fig. SB2), the top AL rules were dominated by Browns and Blacks. The Black-sofa had high connectivity with the Black-cabinet, Brown-cabinet, and background, and Brown-curtain connected to the Brown-plant, cabinet, and background. Owing to the AL order rule, furnishing combinations that are closely related to the style can be identified. If a furnishing combination corresponding to an antecedent is found in a design case, then recommending furniture from the consequent can help create that style.

5. Experts Interviews and Discussions

The main goal of the expert interviews was to assess the reliability, practicality, and applicability of the developed rule generation method and the furnishing pairing rules. Specifically, we conducted semi-structured interviews with experts in the field of interior design to evaluate whether the rules precisely capture the features unique to each style and understand how they can be implemented in real-world interior design practices.

5. 1. Interview setting

Participants. The experts selected for our study all possessed a minimum of five years of practical experience in interior design. These individuals, with an average of 17.2 years in the field, had been directly involved in residential space design projects. Detailed background information on the participants is shown in Table 4.

Table 4 Basic educational and professional details for each participant

Participant ID	Professional experience (years)	Role in project	Educational background
P1	13	Design researcher	Interior design (Doctorate)
P2	5	Designer	Interior design (Masters)
P3	27	Project lead	Interior design (Doctorate)
P4	28	Director	Interior design (Masters)
P5	13	Design researcher	Architecture design (Doctorate)

Data collection. Interviews were conducted online via Zoom and lasted approximately 60 minutes. All the sessions were recorded for subsequent analysis. Interviews were conducted in two stages. In the first section, the participants were asked about their methods of gathering design reference materials, identifying trends, and collecting information on consumer preferences in the context of real-world projects. The second part aimed to elicit participants' evaluations of the research findings and methodologies and discuss how these rules could be beneficial in real-world projects or experiences. Participants listened to a 10-minute introduction on the study's methodology and style-specific pairing rules. Throughout the interview process, the participants continuously reviewed the proposed rules and explored their potential applicability for designers, consumers, and interior design related companies.

5. 2. Interview Findings

5. 2. 1. Theoretical Implications

Validity of the Furnishing Pairing Rule. All interview participants agreed that the rules presented matched well with the images representative of each style, reflecting the common and general understanding of specific styles. For example, P1 believed that the rules, such as the prominence of the "White" keyword in the Modern style, distinctly reflected the characteristics of the style. P2 highlighted that certain item within the rules, such as plant elements in the Natural style, effectively embodied that style. P3 noted that from a color-object perspective, most style-specific rules were trustworthy and aligned with the style images. These insights indicate that our quantitative approach to analyzing interior design elements and furnishing pairing rules is a reliable representation of specific styles.
Assistance in Decision-Making Processes. The furnishing combinations frequently used in each style were confirmed as guidelines, providing directions for consistent styling. Using this methodology, designers and consumers can gain new insights into furnishing choices and decision-making processes using data. Every interviewee agreed that our pairing rules can serve as valuable indicators in decision-making, reflecting public style preferences. For example, P1, P2, P4, and P5 emphasized that the rules informed by data reflecting crowd preferences enable designers to present design narratives that are both relatable and easily understood by the public. Additionally, P2, P3, and P5 recognized the rules as strategic tools capturing crowd preferences and serving as support during the decision-making phase, thereby grounding their choices in quantifiable trends. Consequently, our method can assist designers and consumers in making informed decisions, thereby facilitating a harmonious ambiance that reflects the desired style. They provide clarity on the rationale behind design choices.

5. 2. 2. Managerial and Practical Implications

Discrepancies between Designer and Consumer. Several participants pointed out that the current design process often encounters communication difficulties owing to the disparity in information between experts and non-experts (P2, P4). All participants commonly remain up-to-date with prevailing trends and consumer preferences through design trend reports, exhibitions, and the works of professionals. P2 and P4 pointed out that discrepancies in how designers and consumers visualize and interpret styles often lead to miscommunication, affecting the overall direction of the project. They added that style-specific furnishing pairing rules can facilitate a unified understanding of design preferences and intentions between the parties, promoting agreement in the early stages of a project. Consequently, consumers can articulate their style preferences more clearly, and professionals can develop better design outcomes based on this understanding. Thus, our proposed style-specific furnishing pairing rules can enhance consumer participation in the design process, helping designers establish harmony with consumer preferences.

Guiding Generative AI with Pairing Rules. Our findings support the potential of applying these pairing rules in the form of text-guided prompts for generative AI models, particularly in image generation contexts (P2, P3). Text-to-image generative models, as discussed by Liu and Chilton (2022, April), enable designers and users to create novel visual artworks or reference images based on their input. Participant P3 highlighted the prospect of utilizing these style-specific design element relationships, grounded in large-scale data analysis, to enhance existing AI models. This integration could potentially yield a wide range of practically usable images. In this regard, we applied the style-specific rules as text-guided prompts in the DALL-E3 model to generate images (Betker et al., 2023). The results reveal that detailed input including furniture combinations, as per pairing rules, leads to the manipulation of image-specific styles (as illustrated in Fig. 8).

Figure 8 Application of AL rules in Generative AI for Each Style Living Room

In conclusion, style-specific pairing rules can be utilized as guidelines for refining prompts to achieve desired outcomes. This approach enables the generation of a wider array of stylistic variations, demonstrating the effectiveness of our method in enhancing AI-driven design processes as well as practical applications.

Benefits to Consumer. All participants stated that the style-specific rules would directly benefit consumers, primarily because they assist in formulating a desired design direction even without specialized design knowledge. P4 suggested that consumers can use the rules as a prototype and adjust or add them to establish their design directions. P2, P4, and P5 mentioned that these rules can help consumers consider the pairing of design elements.

P4 and P5 observed that consumers, who often lack extensive design experience, typically concentrate on fragmented or isolated components of a design. Thus, these rules assist in broadening their focus, encouraging an integrated approach to considering comprehensive design elements from structural features to furniture and decorations. P5 highlighted that because the rules are derived from data reflecting the real-life preferences of the crowd, they are inherently user-friendly and easily adaptable. P1 and P3 stated that consumers often adapt their choices to their existing home conditions instead of adapting a comprehensive planning approach; in such cases, the rules assist in maintaining a consistent style.

Benefits to Interior Design Related Company. As online home-furnishing platforms are anticipated to advance in the future, companies in furniture sales, interior construction, finishing, and painting industries are expected to utilize online services. In this context, the participants acknowledged the potential of our research methods as a tool for companies to analyze consumer preferences and design trends (P1, P2, P3, P5). P3 asserted that images with a high number of "scraps" serve dual purposes: they accurately reflect the corresponding style and express user preferences, thereby enhancing a company's insight into consumer behavior and tastes. Furthermore, companies dealing with furniture, lighting, and home accessories can identify consumer-preferred styles and products, affecting industry trends. Additionally, by employing the methods proposed in our research, companies can collect and analyze additional data needed to establish or improve their pairing recommendation systems. Similarly, several experts suggested the possibility of expanding our analytical methods by incorporating additional data. For instance, participants P1 and P2 mentioned that including lifestyle information, such as the size of the living space and family composition (e.g., single-person households, two-person households, and elderly households), would deepen the understanding of consumer preferences. P5 added that if such data were examined over different periods, it would be possible to track historical design trends and predict future trends.

5. 3. Limitation & Future work

Despite the acknowledged strengths of our analytical approach, the participants pointed out several limitations. For example, P4 noted that many designers may already be familiar with furnishing combinations based on their hands-on experience in the field. However, P4 added that owing to a previous lack of comprehensive interior design data available to professional designers, our research findings could serve as a valuable foundation for their decision-making processes. P4 suggested that expanding the scope beyond color-object correlations to include various other factors would considerably enhance the utility and richness of the information. For example, P4 highlighted the importance of architectural shapes, such as ceiling height and window style. Simultaneously, P2 and P5 suggested that additional information related to lifestyle or type of residence could enhance the utility of the rules. Moreover, P3 emphasized that for these rules to be directly applicable in professional design practice, they must comprehensively incorporate aspects such as finishes, materials, lighting, and brand information.

In response to these insights, we propose extending our methodology not only to various residential spaces such as bedrooms and kitchens but also to offices and commercial settings. This expansion will allow us to test the adaptability of our findings across a wider range of interior environments. Furthermore, advancements in object detection technology could facilitate a more detailed and nuanced understanding of interior spaces, allowing for a richer interpretation of complex design elements. Additionally, expanding our analytical framework to incorporate dimensions such as materials, finishes of elements would enable designers to make decisions within a richer context. Finally, applying our methodology in varied cultural settings could reveal unique design principles specific to those cultures, offering a more sophisticated and extensive analysis of interior design that supports more informed and creative decision-making in the field. Furthermore, given the absence of studies on the pairing of interior design elements in South Korea and the emergence of online interior design platforms as a new concept, we recognize an opportunity for pioneering research in this area. Therefore, the availability of data from other countries could serve as a foundation for potentially applying our research across various cultures.

6. Conclusions

In this study, we analyzed eight furnishing styles using actual living room images uploaded to Today's House, South Korea's largest online home furnishing and interior market. We identified significant combinations of furnishings for each style, indicating the importance of analyzing the properties and relationships of design elements, such as furniture (e.g., tables, chairs, sofas, cabinets), fabric (e.g., curtains, rugs), lighting (e.g., floor lamps, ceiling lights), and decorative objects (e.g., plants, art walls).

The contributions of this study can be summarized as follows. First, this study identified a method that can be applied to interior-style analysis and furnishing recommendation situations using the AARM. We proposed a specific approach for interpreting the AARM, making it applicable to various interior-style recommendation scenarios. Second, by comparing the extracted rules and images based on AS, AL, and AC, we confirmed the differences between the results and presented a method for interpreting and using each measurement to make recommendations for interior furnishings. Furthermore, if only combination data regarding the design elements are available, then the method used in this study can identify the relationships between the design elements and extract highly predictive rules. We suggest that the analysis of this method could be enriched by incorporating the latest data or other relevant information, enhancing its applicability not only in interior design but also in other fields requiring analytical and recommendation systems. Finally, validated through expert interviews, the effectiveness of pairing rules in aiding consumers in their furnishing choices and decision-making processes. These rules are informed by crowd preferences and streamline communication between designers and clients, thereby fostering a more collaborative and informed design process. Our study also confirmed the applicability of generative AI in utilizing these rules for informed design visualization. As confirmed in our interviews, interior design is characterized by its unique cultural, social, and personal attributes, necessitating that any research methods and systems be flexible. Therefore, by utilizing the AARM-based method we propose, professional designers can acquire valuable insights.

References

1. Agrawal, R., Imieliński, T., & Swami, A. (1993). Mining association rules between sets of items in large databases. *Proceedings of the 1993 ACM SIGMOD international conference on Management of data*. Doi: 10.1145/170035.170072
2. Cha, S. H., Zhang, S., & Kim, T. W. (2020). Effects of interior color schemes on emotion, task performance, and heart rate in immersive virtual environments. *Journal of Interior Design, 45*(4), 51–65. Doi: 10.1111/joid.12179
3. Chan, C. S. (2001). An examination of the forces that generate a style. *Design Studies, 22*(4), 319–346. Doi: 10.1016/S0142-694X(00)00045-4
4. Garces, E., Agarwala, A., Gutierrez, D., & Hertzmann, A. (2014). A similarity measure for illustration style. *ACM Transactions on Graphics (TOG), 33*(4), 1-9. Doi: https://doi.org/10.1145/2601097.2601131
5. Hasirci, D., & Tuna Ultav, Z. (2020). Mid-Century Modern Furniture Representing Modern Ideals in the Grand National Assembly of Turkey. *Journal of Interior Design, 45*(2), 11–33. Doi: https://doi.org/10.1111/joid.12160
6. Hikmawati, E., Maulidevi, N. U., & Surendro, K. (2022). Rule-ranking method based on item utility in adaptive rule model. *PeerJ Computer Science, 8*, e1013. Doi: https://doi.org/10.7717/peerj-cs.1013
7. Hyun, K. H., & Lee, J. H. (2018). Balancing homogeneity and heterogeneity in design exploration by synthesizing novel design alternatives based on genetic algorithm and strategic styling decision. *Advanced Engineering Informatics, 38*, 113–128. Doi: https://doi.org/10.1016/j.aei.2018.06.005
8. Jeon, Y., Jin, S., Shih, P. C., & Han, K. (2021, May). FashionQ: an ai-driven creativity support tool for facilitating ideation in fashion design. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (pp. 1-18). Doi: https://doi.org/10.1145/3411764.3445093
9. Kadner, F., Keller, Y., & Rothkopf, C. (2021, May). Adaptifont: Increasing individuals' reading speed with a generative font model and bayesian optimization. In *Proceedings of the 2021 chi conference on human factors in computing systems* (pp. 1-11). Doi: https://doi.org/10.1145/3411764.3445140
10. Lee, K., Park, S., & Oh, U. (2021, May). Designing product descriptions for supporting independent grocery shopping of people with visual impairments. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems* (pp. 1-6). Doi: https://doi.org/10.1145/3411763.3451806
11. Liu, Q., Wu, S., & Wang, L. (2017, August). Deepstyle: Learning user preferences for visual recommendation. In *Proceedings of the 40th international acm sigir conference on research and development in information retrieval* (pp. 841-844). Doi: https://doi.org/10.1145/3077136.3080658
12. Liu, T., Hertzmann, A., Li, W., & Funkhouser, T. (2015). Style compatibility for 3D furniture models. *ACM Transactions on Graphics (TOG), 34*(4), 1-9. Doi: https://doi.org/10.1145/2766898
13. Luna, J. M., Fournier-Viger, P., & Ventura, S. (2019). Frequent itemset mining: A 25 years review. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 9*(6), e1329. Doi: https://doi.org/10.1002/widm.1329
14. Nguyen, L. T., Nguyen, P., Nguyen, T. D., Vo, B., Fournier-Viger, P., & Tseng, V. S. (2019). Mining high-utility itemsets in dynamic profit databases. *Knowledge-Based Systems, 175*, 130–144. Doi: https://doi.org/10.1016/j.knosys.2019.03.022
15. Ostrosi, E., Bluntzer, J. B., Zhang, Z., & Stjepandić, J. (2019). Car style-holon recognition in computer-aided design. *Journal of Computational Design and Engineering, 6*(4), 719–738. Doi: https://doi.org/10.1016/j.jcde.2018.10.005
16. Pan, T. Y., Dai, Y. Z., Tsai, W. L., & Hu, M. C. (2017, December). Deep model style: Cross-class style compatibility for 3d furniture within a scene. In *2017 IEEE International Conference on Big Data (Big Data)* (pp. 4307-4313). IEEE. Doi: https://doi.org/10.1109/bigdata.2017.8258459
17. Park, B. H., & Hyun, K. H. (2022). Analysis of pairings of colors and materials of furnishings in interior design with a data-driven framework. *Journal of Computational Design and Engineering, 9*(6), 2419–2438. Doi: https://doi.org/10.1093/jcde/qwac114

18. Person, O., Snelders, D., & Schoormans, J. (2016). Assessing the performance of styling activities: An interview study with industry professionals in style-sensitive companies. *Design Studies, 42*, 33-55. Doi: https://doi.org/10.1016/j.destud.2015.10.001
19. Poldma, T. (2009). Learning the dynamic processes of color and light in interior design. *Journal of Interior Design, 34*(2), 19-33. Doi: https://doi.org/10.1111/j.1939-1668.2008.01017.x
20. Sreedhar, R., Samudrala, N., Tan, N., & Sadalgi, S. (2022, October). Search with Space: Find and Visualize Furniture in Your Space. In *Adjunct Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology* (pp. 1-6). Doi: https://doi.org/10.1145/3526114.3558740
21. Tautkute, I., Możejko, A., Stokowiec, W., Trzciński, T., Brocki, Ł., & Marasek, K. (2017, September). What looks good with my sofa: Multimodal search engine for interior design. In *2017 Federated Conference on Computer Science and Information Systems (FedCSIS)* (pp. 1275-1282). IEEE. Doi: https://doi.org/10.15439/2017f56
22. Tautkute, I., Trzciński, T., Skorupa, A. P., Brocki, Ł., & Marasek, K. (2019). Deepstyle: Multimodal search engine for fashion and interior design. *IEEE Access, 7*, 84613-84628. Doi: https://doi.org/10.1109/access.2019.2923552
23. Wang, X., Zhou, B., Zhang, Y., & Zhao, Y. (2018). Deep style estimator for 3D indoor object collection organization and scene synthesis. *Computers & Graphics, 74*, 76-84. Doi: https://doi.org/10.1016/j.cag.2018.05.008
24. Wisetchat, S., & Stevens, K. A. (2018). Visualizing style differences through 3D animation. *Digital Creativity, 29*(4), 287-298. Doi: https://doi.org/10.1080/14626268.2018.1542316
25. Yaguchi, A., Ono, K., Makihara, E., Ikushima, N., & Nakayama, T. (2022). Multi-Scale Feature Fusion for Interior Style Detection. *Applied Sciences, 12*(19), 9761. Doi: https://doi.org/10.3390/app12199761
26. Yoon, S. Y., Oh, H., & Cho, J. Y. (2010). Understanding furniture design choices using a 3D virtual showroom. *Journal of Interior Design, 35*(3), 33-50. Doi: https://doi.org/10.1111/j.1939-1668.2010.01041.x
27. Awad, N. A., & Mahmoud, A. (2021). Analyzing customer reviews on social media via applying association rule. *Computers, Materials and Continua, 68*(2), 1519-1530. Doi: https://doi.org/10.32604/cmc.2021.016974
28. Shiau, R., Wu, H. Y., Kim, E., Du, Y. L., Guo, A., Zhang, Z., ... & Zhai, A. (2020, August). Shop the look: Building a large scale visual shopping system at pinterest. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (pp. 3203-3212). Doi: https://doi.org/10.1145/3394486.3403372
29. Redmon, J., & Farhadi, A. (2018). Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*. Doi: https://doi.org/10.48550/arXiv.1804.02767.
30. Betker, J., Goh, G., Jing, L., Brooks, T., Wang, J., Li, L., ... & Ramesh, A. (2023). Improving image generation with better captions. *Computer Science*. https://cdn. openai. com/papers/dall-e-3. pdf, 2, 3. Doi: https://cdn. openai. com/papers/dall-e-3. pdf.
31. Guo, S., Shi, Y., Xiao, P., Fu, Y., Lin, J., Zeng, W., & Lee, T. Y. (2023). Creative and progressive interior color design with eye-tracked user preference. *ACM Transactions on Computer-Human Interaction, 30*(1), 1-31. Doi: https://doi.org/10.1145/3542922
32. Liu, V., & Chilton, L. B. (2022, April). Design guidelines for prompt engineering text-to-image generative models. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (pp. 1-23). Doi: https://doi.org/10.1145/3491102.3501825
33. Iqbal, S., Khan, R., Khan, H. U., Alarfaj, F. K., Alomair, A. M., & Ahmed, M. (2022). *Association Rule Analysis-Based Identification of Influential Users in the Social Media*. Doi: https://doi.org/10.32604/cmc.2022.030881