To see and then to believe: how image affect tenant decision-making and satisfaction on short-term rental platform

Xue Yang1 · Miao Tian2

Accepted: 23 September 2022
© The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2022

Abstract
Home sharing is a new industry that was born with the development of sharing economy. The online short-term rental platform is an important carrier for home sharing. On the short-term rental platform, house images are an essential way to display the overall situation of the house, and one of the main channels for tenants to obtain house information. This paper studies the relationship between house images’ colors and contents and tenant booking decision-making and satisfaction. By utilizing image mining techniques on the data obtained from a popular short-term rental platform in China, this research reveals that the color richness of house images has a significant negative relationship with both tenant booking decision-making and tenant satisfaction. What’s more, both household and leisure content displayed in house images has significant positive relationships with tenant booking decision-making. Our work supplements the research on the impact of house images on home sharing and provides meaningful guidance for both the short-term rental platforms and the landlords.

Keywords Sharing economy · Online short-term rental · Home sharing · House image · Image mining

Xue Yang
yangxue@nju.edu.cn
Miao Tian
tianmiao0918@163.com

1 Nanjing University, Nanjing, China
2 JD.Com, Beijing, China

Published online: 18 October 2022
1 Introduction

Thanks to the rapid development of information technology, the sharing economy has prospered in recent years. The sharing economy is characterized by ownership sharing and can help integrate massive and decentralized resources to meet diverse needs. From the perspective of market structure, life service, production capacity, and transportation are the top three areas of sharing economy. Peer-to-Peer (P2P) accommodation, also known as home-sharing, is an important part of life service sharing. Nowadays home sharing has become the choice of more and more people when travelling. There are more than 150 million users covering more than 65,000 cities on Airbnb, the most famous online platform that offers home sharing service in the world[1]. According to a study by Morgan Stanley, 49% of Airbnb users of the home-sharing service used it as an alternative to a traditional hotel[2].

The online short-term rental platform is an important carrier for home sharing. Different from the traditional accommodation industry, tenants use the information provided by the landlords on the online short-term rental platform to help them evaluate the houses, instead of investigating the house offline before making a choice. The information includes house description, house images, online tenant reviews, and so on. home sharing is also different from hotel for it is not so standardized, and that makes it more important to utilize the online information. Among the information, house images are the most natural and effective source to show the true conditions of the house. As a visual hint, house images can attract consumers’ attention [3]. There are many attributes of an image, such as the color richness (the number of dominant colors in an image), the number and category of items in the image, that is, the content of the image, etc. Different attributes may convey different information and have different impacts on consumer’s impression of the house, hence influence consumer’s booking decision. So the revenue of the houses may also be influenced. Therefore, it is important to study whether the image attributes influence tenant decision-making and the mechanisms behind it. These studies can not only help increase the sales of home sharing, but also guide the short-term rental platforms and the landlords to improve the operation, thereby helping to improve tenants’ experience and consumption quality.

Previously, various research has studied the mechanism of how images influence consumer behavior and decision-making in online transactions. They found that product images can increase consumers’ confidence in judgment by remedying the lack of haptic information of products [4], and detailed images showing complementary items placed together (e.g. pairing t-shirt and pants together on a model) have positive impacts on consumers’ purchase intention [5, 6]. Furthermore, products with verified photos (such as taken by the platform’s photographers) may generate additional revenue because of their high image quality [7]. However, related research in the field of home sharing is still limited in the existing literature, especially the research on the relationship between house images’ detailed attributes, such as the color richness and image contents, and tenant booking decision-making and satisfaction.

Based on the former discussion, we put forward the following research questions:
(1) Is the color richness of house images on the short-term rental platform related to the tenants’ booking decision-making and satisfaction?
(2) Is the content of house images on the short-term rental platform related to the tenants’ booking decision-making and satisfaction?
(3) Is the relationship between house images’ contents and tenant booking decision-making and satisfaction affected by house images’ color richness?
(4) We obtained housing information from a popular short-term rental platform in China, and then used Microsoft Azure’s Computer Vision analysis technique to analyze the acquired house images regarding their color and contents. The Sentiment Analysis of iFLYTEK Open Platform was used to analyze the consumer reviews.

In the next section we will review the previous literature in related fields. In Sect. 3 we put forward the main hypotheses of this article. Then we introduce the research methods and explain the data sources, variables and models in Sect. 4, and analysis results in Sect. 5. Finally, we conclude this research with discussion, theoretical and practical contributions and limitations in Sect. 6.

2 Literature review

2.1 Factors addressing information asymmetry in sharing economy

The sharing economy is an economic model based on sharing underutilized assets between peers without the transfer of ownership via an online mediated platform. The assets can be spaces, skills, or stuff [8]. When the shared asset is space, it can be called home sharing. Therefore, home sharing also faces the same dilemma as traditional online transactions, that is, consumers cannot directly experience the goods. Many previous researches studied how online transaction platforms can help address this issue.

First of all, the reputation system, including the online review and the rating system, is a powerful tool to help overcome the shortcomings of online transaction. The online review plays the most important role [9–12]. The number [9] and content [10] of reviews both have influence on consumer purchase decision-making. The study of Thomas et al. [11] shows that the review credibility has a significant positive effect on consumer’s purchase intention. Their work also shows that the accuracy, completeness, review quantity, reviewer expertise, product/service rating and website reputation can positively affect review credibility. However, convincing signals other than online reviews, such as the product quality information cues, can significantly reduce consumer’s reliance on online reviews [12]. In addition, the presentation of the product [13], the seller’s personal photo [14], the number of product views and the size of the product image [15] will also influence the consumer behavior.

However, sharing economy is very different from traditional online transaction, for there are three main roles on it: peer providers, platform, and peer consumers. Therefore, in addition to the aforementioned factors, there are some other factors that
influence consumer experience in sharing economy. In home sharing, information disclosure (including information source, information content, information presentation format and the quality of information) has influence on the consumer purchase behavior [16]. Besides, hosts’ photographs [17], guest–host interactions [18], and social distance [19] also affect consumers’ experience in home sharing. The product image has been proved to be useful for addressing the information asymmetry about the products. We will discuss it in detail in the next section.

2.2 The influence of images on consumer behavior in online transactions

The product image is an important factor affecting the consumer choice. In online transactions, because consumers cannot use a variety of senses, such as touch, to evaluate products as they can do in traditional offline transactions, the product image is the main source for consumers to obtain intuitive product information. Peck and Childers [4] reveal that product images can make up for the lack of haptic information of products, thereby increasing consumers’ willingness to buy. Other research further shows that the product or property’s image has a great influence on consumer purchase decision-making [20, 21].

The product image contains color attributes and content attributes. As for the color attributes, warm-colored images, images with higher brightness, and images with consistent color cues and color-related textual cues are more acceptable to the tenants in home sharing [7, 22]. The color complexity of advertising images has a positive significant association with click-through rates but a negative relationship with conversion rates in online transactions [23].

As for the content attributes, Yoo and Kim [5] find that complementary apparel items should be placed together (e.g., pairing t-shirt and pants together on a model) on the websites to produce favorable consumer shopping outcomes. Their research suggests that it’s better not to present the model’s face with the product. Another research of them [6] indicates that product presentation with a relevant consumption background is more effective in evoking mental imagery than one with a solid white background, thus increases consumers’ behavioral intentions. These two pieces of research reveal that detailed images and images presenting complementary items have positive impacts on consumers’ purchase intention. Besides, feature complexity (contain dense perceptual features) vs. design complexity (have an elaborate creative design) hurts/enhances attention to the brand and attitude toward the ad [24]. In home sharing, the houses presenting outdoor image as the first image receive lower reservation compared to those presenting indoor image first [25].

The house images tell tenants how the house looks like. Tenants’ preference on the images is closely related to their preference on the houses. Although the above mentioned research has examined the role of product images on sharing platforms and found that product images have impacts on consumer decision-making, little research about home sharing focused on the detailed information of the house represented by images, such as colors and contents. What’s more, existing literature only studied some basic color elements, such as hue, saturation and lightness of house images, rather than the harmony of multiple colors.
in the images. As for the image contents, although many researchers have studied the item display in product pictures, few research studied the items in the images, such as the number and category of items, in home sharing. The current research studies the relationship between these information and tenants’ booking decision and satisfaction. What characteristics of a house image are more or less attractive to consumers? This issue can provide a reference on how to arrange and display the houses for the platforms and the landlords to help them obtain higher benefits.

3 Hypotheses development

Houses in home sharing are different from hotels in many aspects, such as the ability to bring pets and the opportunity to encounter hosts’ pets, atmosphere, flexibility, value for money, and quality assurance [26]. Another difference is the standardization. Most traditional hotels offer standardized rooms. A house on the short-term rental platform is often the landlord’s own house. In most instances, it is decorated and arranged according to the landlord’s preferences and ideas. So the houses on short-term rental platforms are always different from each other. When there are more choices in terms of decorations and equipment supplied to tenants, we are interested if these factors are related to tenant decision-making before actual consumption, e.g., booking decision, and tenants’ satisfaction toward the house after experiencing the actual product.

The quality of the services provided in home sharing cannot be confirmed until being experienced [27]. Hence tenants need to gather information provided online to help them evaluate the houses. House images help tenants build their first impressions, especially the image displayed in the first page. Most people will see all the images when seeking a P2P accommodation. House owners usually choose the most representative image to place in the first spot of image section in order to attract users’ attention when they view multiple houses in the list page. And the first image usually shows the overall view of the house. According to the primacy effect [28], people tend to remember the first piece of information they encounter better than information presented later on. Hence as an essential factor in building tenants’ first impression of a house, the first image has a more substantial and lasting effect compared to other images. By browsing the house images on the short-term rental platform, tenants can intuitively obtain information about the decoration style and facilities, thus having a judgment on the house. Even after experiencing the actual house after consumption, as the images can largely represent the house, their attributes may still be closely related to tenants’ responses. Among all the image attributes, color richness, and image contents are essential expressions of house decoration style and facilities. So, we focus the research on the relationship between the house images’ colors and contents and tenant booking decision-making, and further, tenant satisfaction.

The conceptual model of this article is shown as Fig. 1.
3.1 Relationship between image color richness and tenant purchase experience

Many previous studies have revealed that colors have a strong association with mood of humans [29–31] and number of colors have strong emotional effects [32]. Alfakhri et al. [33] found that color is an important factor in affecting customers’ aesthetic perceptions in hotelscape. Interior colors of houses may affect one’s emotion, happiness, and vividness [34].

In this study, we use color richness to indicate the number of dominant colors in an image. The more dominant colors there are in an image, the higher color richness the image has. An image can create the impression of dominant color when the colors have similar hues but different intensities or saturation [35], and Chen et al. [36] developed it into spatially adaptive dominant colors. So we can infer that the more dominant colors an image has, the higher hue contrast the image has. Many previous studies revealed that color harmony decreased with hue contrast and increased with hue similarity [37–40]. Therefore, images with high color richness may make the house look unharmonious and even messy. According to Judd and Wyszecki [41], a color harmony means that multiple colors seen in neighboring areas produce a pleasing effect. The harmonious color atmosphere of the interior can delight people’s spirit. Hence, the higher a house image’ color richness is, the less pleasing the house is. Therefore, we infer that people prefer houses with low color richness, so as to obtain psychological pleasure during the housing experience. What’s more, people usually book short-term rental houses for casual traveling which makes pleasant experience even more necessary in this scenario.

Therefore, we hypothesize that when people see a house image with lower color richness, they are more likely to have a good impression on the house, and have higher possibility to book the house.

Previous work supported that perceived performance exerts direct significant influence on satisfaction [42]. According to Shin et al. [43], enjoyment is the most important push factor that improves consumer satisfaction in home sharing. So we identify that the color richness which tenants experience offline may affect
tenants’ perceived performance of the house, thus has impact on tenant satisfaction. As most short-term rental platforms have requirements for the authenticity of house images, the house images tell tenants how the house really looks like. Tenants’ preference on the images is also their preference on the houses. For example, after tenants choose houses with particular type of color richness based on the house image, they are likely to be satisfied with the chosen house which have features consistent with the images. Hence, it infers that the image color richness can affect tenant satisfaction even after decision-making and offline living experience.

Therefore, we hypothesize that tenants prefer houses with lower color richness in images on short-term rental platform:

**Hypothesis 1a** Tenants’ booking decision is negatively related to house images’ color richness.

**Hypothesis 1b** Tenants’ satisfaction is negatively related to house images’ color richness.

### 3.2 Relationship between image household content and tenant purchase experience

The contents of the house images, that is, the items and layout displayed, are another main type of information that consumers can obtain from the image. The differences of the contents of the house images may come from two ways. One is that the houses themselves are different in size, structure, furniture, and other aspects. The other is the difference in shooting angles and so on.

The image content consists of various items displayed in the image. Household content is a kind of valuable content displayed in the house images. According to the Thomson Reuters Business Classification (TRBC) [44], household goods contain consumer electronics, appliances, tools & housewares, and home furnishing. In this article, we define items such as furniture and home appliances that can meet the basic needs of life and provide convenience to tenants as *household goods*. The more household goods in the house displayed in the image, the more useful items the house may have, and the more convenient and comfortable the tenant’s living in the house is likely to be. Additionally, images with more household goods convey more information about the house, which tenants can use to help them make the assessment. So it can help the house gain trust and preference from tenants and the tenant may tend to book the house.

Several studies have found that short-term rental house’s lodging service quality is positively related to consumer satisfaction [45, 46]. That a house has more household goods in its image, indicates that it may actually has more facilities. More facilities make it more convenient for living, therefore, the house may have higher lodging service quality. So tenants may be more satisfied with such a house. Thus, we hypothesize that:
Hypothesis 2a Tenants’ booking decision is positively related to the number of household goods displayed in a house’s image.

Hypothesis 2b Tenants’ satisfaction is positively related to the number of household goods displayed in a house’s image.

3.3 Relationship between image leisure content and tenant purchase experience

In addition to household content, leisure content is another important content category that impacts tenants’ decision-making. According to the Thomson Reuters Business Classification (TRBC) [44], leisure products contain toys, juvenile products, and recreational products. In this article, we define items such as decorations and toys as leisure products. The delicate decoration is a part of the construction of affective home feeling. Most people have a passion for beauty. Perception of beauty and aesthetically pleasing stimuli are part of sensory appeal of customer experience [47]. Leisure products such as toys, plants and hanging pictures can meet the aesthetic and relaxation needs of tenants. On the one hand, leisure products can enhance the atmosphere of life, make people happy, and can give tenants a more luxurious aesthetic experience [48]. On the other hand, placing leisure products in the house also reflects the landlord’s intentions to provide better services, thus enhancing tenants’ trust toward the house. So tenants may prefer houses with more leisure products in the images. More leisure products in the house also improve the house’s service quality, making tenants more satisfied after living in such a house. Thus, we hypothesize that:

Hypothesis 3a Tenants’ booking decision is positively related to the number of leisure products displayed in a house’s image.

Hypothesis 3b Tenants’ satisfaction is positively related to the number of leisure products displayed in a house’s image.

3.4 Implications of color richness’s moderating effects

Based on the previous discussion, tenants prefer houses with more contents in the images, including household and leisure content. However, as discussed in Sect. 3.1, tenants do not like houses with high color richness, because of the harmonious [41]. Therefore, the decision of tenants’ booking a house with more household goods or leisure products in the image may be weakened if its image is too colorful. We hypothesize that the color richness will negatively moderate the correlation between image content and tenant decision-making. Thus, we hypothesize that:

Hypothesis 4a The relationship between image content and tenants booking decision-making is negatively moderated by the image’s color richness.
Hypothesis 4b The relationship between image content and tenant satisfaction is negatively moderated by the image’s color richness.

4 Empirical research

4.1 Research setting

To study the relationship between house images and tenant decision-making, we collect data from a leading online short-term rental platform in China. It provides users with short-term rental accommodation services and is a leading enterprise in the field of home sharing in China. It was established in 2012 and officially launched in August 2012. As of December 2018, the number of short-term rental properties on this platform has exceeded 500,000 worldwide, covering 60 countries, regions on five continents, and more than 710 cities. The platform implements several localization measures attempting to meet China’s unique social, political, economic, cultural and other national conditions, such as installing smart locks for landlords, purchasing insurance for both parties, and launching the cleaning service on July 5, 2016. This platform has gained a high market share and is currently one of the four major short-term rental platforms in China.

We obtained data from the short-term rental platform of 9,474 houses from July 2012 to May 2017. The data comes from two sources:

(1) Listing page (Fig. 2 a, b). From the website of every house, we obtained ID, title, image displayed in the initial page (viewers need to click to browse other images), location, price, size, unit type, reviews, and rating score of the house.

(2) Landlord page (Fig. 3). From the landlord page, we obtained the landlord’s listing and release time of every house.

We then use the Computer Vision analysis to analyze the house images and use Sentiment Analysis to analyze the reviews of the houses.

4.1.1 House images analysis

With the rapid development of computer technology, artificial intelligence (AI) has become an important method for online platform research. In this article, we use the Computer Vision analytics to analyze the images. Computer vision tasks include methods for acquiring, processing, analyzing and understanding digital images, and extraction of high-dimensional data from the real world in order to produce numerical or symbolic information. Deep learning has led to very good performance on visual recognition. Among different types of deep neural networks, convolutional neural networks (CNNs) have been most extensively studied and used in computer vision tasks. Microsoft’s Computer Vision analytics which we used to analyze the images is also based on CNNs.
The Computer Vision analysis is implemented in the API of Azure Cognitive Services of Microsoft. This article uses the Computer Vision API to analyze the first image of the house obtained from the listing page. The short-term rental platform allows landlords to display several images on the listing page, and the tenants need to click a button to browse the next image. The first image usually shows the overall view of the house. In this study, we focus on the first image which tenants can see right after entering a listing page. According to the primacy effect, people tend to
To see and then to believe: how image affect tenant…

remember the first piece of information they encounter better than information presented later on. Shteingart et al. [49] also find that primacy effect is also prominent in decision making based on experience in a repeated-choice paradigm. Hence as an essential factor in building tenants’ first impression of a house, the first image has a more substantial and lasting effect compared to other images.

The "Describe Image" function analyzes images and generates readable sentences describing their contents. The algorithm returns multiple descriptions based on different visual functions, and each description has a confidence score. The final output is a list of descriptions ordered from high to low. For each image, the results include the foreground dominant color, background dominant color, dominant colors, and tags describing the contents of the image. The analysis mainly identifies and marks 12 dominant colors, including black, blue, brown, gray, green, orange, purple, red, teal, white, and yellow. The foreground and background dominant colors are a single color that best represent the house. The variable "dominant colors" displays all the dominant colors identified on the image.

The variable "image categories" are corresponding categories generated in the process of classifying images. The analysis uses category classification with a parent/child genetic hierarchy to identify and classify the entire image. The statement and credibility are a list, which is composed of multiple descriptions and the credibility score of the description. The results include the contents of the image and attaches multiple tags to the image. Each tag is generally a single word. Those tags contain descriptions of the attributes, colors, actions, items, and states of the image.

Fig. 3 A Landlord Page
For example, the content analysis for the house image of Fig. 4 generates the results as following:

(1) Foreground dominant color: "white";
(2) Background dominant color: "brown";
(3) Dominant colors: "brown, grey, white";
(4) Description: "a bedroom with a bed and a chair in a room";
(5) Tags: "indoor, bed, room, table, chair, wooden, window, bedroom, sitting, wood, small, hotel, large, desk, white, decorated, mirror, made, double, living".

All the tags are manually divided into three categories — household goods, leisure products and others based on their attributes. For example, "bed, table, chair, brown, window, desk, mirror" are household goods, "wooden, wood, decorated, " are leisure products.

We analyzed images of our 9,474 houses and got the corresponding output. After excluding false and invalid values, finally, we use the data set of 9,183 houses operating between July 2012 and May 2017 in the main analysis for empirical research, covering 48 cities in China.

### 4.1.2 House reviews analysis

Because the platform analyzed in this article is a Chinese short-term rental platform, most reviews on this platform are written in Chinese. We use the Sentiment Analysis method to analyze the sentiment of the reviews. The Sentiment Analysis is implemented in the API of iFLYTEK Open Platform. iFLYTEK Open Platform was launched in 2010 by iFLYTEK as China’s first Artificial Intelligence open platform for Mobile Internet and intelligent hardware developers (HIT-SCIR), and the Sentiment Analysis is a highly accurate and widely used API. Zhu et al. [50] used this API to identify the sentiment of text files of Weibo, a Chinese social network.
To see and then to believe: how image affect tenant…

platform. The document level sentiment classification is based on a neural network model that learns vector-based document representation in a unified, bottom-up fashion [51]. The model first learns sentence representation with convolutional neural network (CNN) or long short-term memory. Afterwards, semantics of sentences and their relations are adaptively encoded in document representation with gated recurrent neural network. Experimental results show that this neural model shows superior performances over several state-of-the-art algorithms. The Sentiment Analysis of iFLYTEK Open Platform calculates the probability that a piece of text is positive, negative, and neutral simultaneously, while these three probabilities add up to one. Not all the houses in the dataset have tenant reviews. We analyzed 38,216 reviews of 4,376 houses that has tenant reviews.

4.2 Variables

We generate 14 variables as shown in Table 1. The variables are explained as follows:

(1) **Reviews**: As the number of bookings is usually not available on the platform, researchers usually use review rate, which ranges from 18.6 [52] to 72%, to convert reviews to estimated bookings [9]. The study of Ye et al. [53] also supports the hypothesis that the number of reviews is a proxy for online sales, so this article uses the number of reviews to measure tenant booking decision-making.

(2) **Rating score**: Tenants may not only express their appreciation of the house but also their dissatisfaction with the house, we use rating scores and reviews sentiment to measure tenant satisfaction. While writing reviews, tenants need

| Variable Name              | Definition                                                                 |
|----------------------------|-----------------------------------------------------------------------------|
| Reviews                    | The number of reviews of the house                                           |
| Rating score               | The rating score of the house                                               |
| Reviews sentiment          | The overall sentiment of the reviews of the house                            |
| Color richness             | The number of dominant colors of the image                                  |
| Household content          | The number of tags representing household goods of the image                |
| Leisure content            | The number of tags representing leisure products of the image               |
| Month release              | Number of months the house has been online                                  |
| City GDP                   | GDP of the city where the house is located. (billion yuan)                   |
| Price                      | The price of the house. (yuan)                                              |
| Size                       | The size of the house. (m²)                                                 |
| Rooms                      | The number of rooms the entire house has                                    |
| Living rooms               | The number of living rooms the entire house has                             |
| Bathrooms                  | The number of bathrooms the entire house has                                |
| Kitchens                   | The number of kitchens the entire house has                                 |
| Balconies                  | The number of balconies the entire house has                                |
to give a five-star rating on five aspects of the house: cleanliness, descriptive match, traffic and location, security, and cost-effectiveness. Then according to the platform’s algorithm, all the ratings of a house is integrated to get the rating scores covering these five aspects, and the weighted average of the five ratings is the final house rating score. According to the platform rule, the rating of a house is displayed on the platform only when the house has more than 4 reviews.

(3) **Reviews sentiment:** We use the reviews sentiment as another measure of tenant satisfaction. For each review, there is the probability of it being positive, negative and neutral. We choose the sentiment with biggest probability as the sentiment of the review. For example, if a review’s probability of being positive, negative and neutral is 0.723, 0.275 and 0.002 separately, we set the sentiment of the review as positive. Then we count the number of each sentiment of a house, and use \((\text{number of positive sentiment} + 1) / (\text{number of negative sentiment} + 1)\) as the review sentiment of the house. For example, if a house has 2 positive reviews and 1 negative review, then the review sentiment of the house is 1.5.

(4) **Color richness**: the number of colors listed in the variable "dominant colors" which is generated by the Computer Vision analysis. It measures the number of dominant colors contained in the image. Figure 5 shows two images with color richness of 1 and 3, respectively.

(5) **Household content**: as introduced before, the Computer Vision analysis generates tags for every image, and we divide them into three categories — household goods, leisure products and others. We use the number of tags representing household goods which contain furniture, household appliances and so on, to measure the household content of the image.

(6) **Leisure content**: we use the number of tags representing leisure products contain flowers, paintings, dolls and so on, to measure the decorative content of the image.

(7) Control variables: in order to avoid omitted-variable bias, several control variables are chosen in the regression model. The longer the house is online, the more likely there will be more orders. So month release should be controlled. City GDP reflects the local living standard, thus may affect the transaction of the
houses there. House information, such as *price, size*, number of *rooms, living rooms, bathrooms, kitchens* and *balconies*, is the important factor that tenants will consider when making decision. Therefore, these factors should be controlled.

5 Data analysis and results

5.1 Descriptive statistical analysis

In order to further understand the characteristics of data distribution, this article conducted a descriptive statistical analysis on some variables. From the distribution of reviews (Fig. 6a), we can see that 4818 houses have no reviews, which accounts for more than 50% of all houses. In order to better observe the distribution of reviews, we eliminated the data with zero reviews and plotted another statistical graph (Fig. 6b). It can be seen that more than 85% of houses have less...
than 20 reviews, and houses with more than 20 reviews account for less than 25% of total houses. Few houses have a lot of bookings. This distribution is normal in the market. Consistent with the long-tail theory, tenants’ demand in short-term rental market is mainly concentrated in a relatively small number of houses. Tenants usually have similar requirements for geographical location, price, decoration, facilities, transportation and other factors. However, houses that meet these requirements are limited. So there are few houses with many bookings.

Descriptive statistical analysis of variables is shown in Table 2. Table 3 presents the correlations among the variables.

### Table 2  Descriptive statistical analysis

|                  | N   | Min | Max  | Mean | Std. Dev |
|------------------|-----|-----|------|------|----------|
| Reviews          | 9,183 | 0   | 205  | 5.07 | 12.603   |
| Rating score     | 2,433 | 3.0 | 5.0  | 4.85 | .193     |
| Reviews sentiment| 4,376 | 0.33| 39   | 6.45 | 6.83     |
| Color richness   | 9,183 | 0   | 3    | 1.66 | .716     |
| Household content| 9,183 | 0   | 19   | 6.66 | 2.302    |
| Leisure content  | 9,183 | 0   | 11   | 2.15 | 1.610    |
| Month release    | 9,183 | 6   | 64   | 20.87| 13.516   |
| City GDP         | 9,183 | 24.48| 28,183.51 | 9688.19 | 8620.326 |
| Price            | 9,183 | 8   | 12,888 | 348.46 | 514.310  |
| Size             | 9,183 | 2   | 2600  | 68.59 | 78.182   |
| Rooms            | 9,183 | 0   | 20   | 2.09 | 1.539    |
| Living rooms     | 9,183 | 0   | 9    | 1.06 | .812     |
| Bathrooms        | 9,183 | 0   | 26   | 1.40 | 1.210    |
| Kitchens         | 9,183 | 0   | 11   | .82  | .436     |
| Balconies        | 9,183 | 0   | 18   | .90  | .881     |

The dataset in this research contains 9,183 houses, however, not all the houses get reviews from tenants. Only 4,376 houses have tenant reviews in the dataset, so the number of reviews sentiment is 4,376. In addition, for the reason that a house’s rating score will be displayed on the listing page only when the house has more than 4 reviews, there are only 2,433 houses have rating score.

### Table 3  Correlation table

| (1) | (2) | (3) | (4) | (5) | (6) |
|-----|-----|-----|-----|-----|-----|
| Reviews | 1.000 |    |     |     |     |
| Rating score | 0.171*** | 1.000 |     |     |     |
| Reviews sentiment | 0.729*** | 0.271*** | 1.000 |     |     |
| Color richness | –0.074*** | –0.050* | –0.076*** | 1.000 |     |
| Household content | 0.051*** | 0.043* | 0.053*** | –0.007 | 1.000 |
| Leisure content | 0.097*** | 0.083*** | 0.094*** | –0.023* | 0.249*** | 1.000 |

*** p < 0.001, ** p < 0.01, * p < 0.05
5.2 Regression analysis

We apply multivariate linear regression analysis to examine how the attributes of house images is related to the tenant decision-making. In examining the influence on ratings, we use the observations whose rating is more than 0, because a house can get a rating only when it has more than 4 reviews. In examining the influence on reviews sentiment, we use the houses which have at least one review. The analysis results are shown in Tables 4 and 5.

(1) The relationship between house images’ color richness and tenant booking decision-making and satisfaction. Table 4 reports the estimate for number of reviews. The result shows that house images’ color richness is significantly negatively correlated to the number of reviews of the house (β = −1.075, \( p < 0.001 \)). Hypothesis 1a is supported. Table 5 shows that color richness is significantly negatively correlated to both ratings and reviews sentiments of the houses (β = −0.01, \( p < 0.1 \) and β = −0.225, \( p < 0.05 \)), indicating that it is negatively correlated to the tenant satisfaction. Thus, this result provide evidence in support of Hypothesis 1b.

(2) The relationship between house images’ household content and tenant booking decision-making and satisfaction. According to Table 4, house images’ household content is positively and significantly correlated with the house’s number of reviews (β = 0.126, \( p < 0.05 \)), providing evidence in support of Hypothesis 2a. The more household contents a house image has, the more inclined tenants are to book this house. While according to Table 5, household contents have no significant relationship with tenant satisfaction. Household content reflects the facilities and equipment of the house. The insignificance may be because the facilities and equipment are relatively objective. If there is a microwave in the house picture, there is a microwave in the house. So the perceived ease of use of a house assessed after the real experience is not much different from the perceived ease of use estimated from the household content of the house’s picture. The facilities and equipment are fundamental things that need to be considered when booking an accommodation, and tenants will book a house only when they think the facilities of the house can meet their needs. Hence the satisfaction level of all booked house is generally similar and the offline experience will not change it a lot, although these houses may have different facilities and equipment. So the household content does little in influencing tenants’ satisfaction.

(3) The relationship between house images’ leisure content and tenant booking decision-making and satisfaction. The regression result of Table 4 shows that leisure content of house images has a positive and significant correlation with the house’s number of reviews (β = 0.65, \( p < 0.001 \)). This result is consistent with hypothesis 3a. While according to Table 5, leisure content has no significant effect on tenant satisfaction. The reason for this result may be similar to the insignificance of household content’s effect on tenant satisfaction. The leisure content of the house image is relatively objective and will not differ a lot from what the house really has. So the satisfaction level of all booked house is generally similar and the offline experience will not change it a lot, although these
houses may have different leisure products. So the leisure content does little in influencing tenants’ satisfaction.

(4) The moderating effect of color richness. Table 6 reports the results of the moderating effect of color richness on image content’s relationship with tenant booking decision-making and satisfaction. According to Table 6, both household goods

![Springer](https://image.pollinations.ai/prompt/Springer)
Table 5 Regression results on tenant satisfaction

|                        | Rating score | Reviews sentiment |
|------------------------|--------------|------------------|
|                        | (1)          | (2)              | (3)          | (4)          | (5)          | (6)          |
| **Image color attributes** |              |                  |              |              |              |              |
| Color richness         | −0.010‡      | −0.010‡          | −0.236*      | −0.225*      |              |              |
|                        | (0.005)      | (0.005)          | (0.101)      | (0.101)      |              |              |
| **Image content attributes** |            |                  |              |              |              |              |
| Household content      | 0.001        | 0.000            | 0.023        | 0.021        |              |              |
|                        | (0.002)      | (0.002)          | (0.032)      | (0.032)      |              |              |
| Leisure content        | 0.002        | 0.002            | 0.082        | 0.078        |              |              |
|                        | (0.002)      | (0.002)          | (0.045)      | (0.045)      |              |              |
| **Time and region reviews** |            |                  |              |              |              |              |
| reviews                | 0.002***     | 0.002***         | 0.291***     | 0.290***     | 0.290***     |              |
|                        | (0.000)      | (0.000)          | (0.004)      | (0.004)      | (0.004)      |              |
| Month release          | −0.004***    | −0.004***        | −0.004****   | 0.011        | 0.011        | 0.011        |
|                        | (0.000)      | (0.000)          | (0.006)      | (0.006)      | (0.006)      |              |
| City GDP               | 0.000        | 0.000            | 0.000        | 0.000        | 0.000        | 0.000        |
|                        | (0.000)      | (0.000)          | (0.000)      | (0.000)      | (0.000)      | (0.000)      |
| **House features**     |              |                  |              |              |              |              |
| Price                  | −0.000       | −0.000           | −0.000       | 0.000        | 0.000        | 0.000        |
|                        | (0.000)      | (0.000)          | (0.000)      | (0.000)      | (0.000)      | (0.000)      |
| Size                   | −0.000       | −0.000           | −0.000       | −0.003*      | −0.004*      | −0.003*      |
|                        | (0.000)      | (0.000)          | (0.001)      | (0.001)      | (0.001)      |              |
| Rooms                  | 0.003        | 0.003            | 0.003        | 0.237**      | 0.245**      | 0.245**      |
|                        | (0.005)      | (0.005)          | (0.085)      | (0.085)      | (0.085)      |              |
| Living rooms           | 0.023***     | 0.023**          | 0.237***     | 0.187        | 0.160        | 0.167        |
|                        | (0.007)      | (0.007)          | (0.130)      | (0.131)      | (0.131)      |              |
| Bathrooms              | −0.013‡      | −0.013‡          | −0.013*      | −0.420***    | −0.417***    | −0.417***    |
|                        | (0.007)      | (0.007)          | (0.100)      | (0.100)      | (0.100)      |              |
| Kitchens               | 0.036**      | 0.036**          | 0.036**      | 0.292        | 0.276        | 0.277        |
|                        | (0.013)      | (0.013)          | (0.222)      | (0.222)      | (0.222)      |              |
| Balconies              | 0.014*       | 0.014*           | 0.014*       | 0.164        | 0.161        | 0.160        |
|                        | (0.006)      | (0.006)          | (0.102)      | (0.102)      | (0.102)      |              |
| _cons                  | 4.888***     | 4.865***         | 4.880***     | 2.512***     | 1.862***     | 2.225***     |
|                        | (0.020)      | (0.021)          | (0.023)      | (0.329)      | (0.348)      | (0.384)      |
| R²                     | 0.111        | 0.111            | 0.112        | 0.540        | 0.540        | 0.541        |
| (Adjusted R²)          | (0.106)      | (0.106)          | (0.107)      | (0.539)      | (0.539)      | (0.540)      |
| Obs                    | 2433         | 2433             | 2433         | 4376         | 4376         | 4376         |

Standard errors are in parenthesis

*** p < 0.001, ** p < 0.01, * p < 0.05, ‡ p < 0.1

Not all the houses in our dataset have tenant reviews. Only 4,376 houses have tenant reviews in the dataset. In addition, for the reason that a house’s rating score will be displayed on the listing page only when the house has more than 4 reviews, there are only 2,433 houses have rating score.
### Table 6  Estimation of moderate effect

|                  | Reviews |         |         |
|------------------|---------|---------|---------|
|                  | (1)     | (2)     |         |
| **Image content attributes** |         |         |         |
| Household content | 0.126*  | 0.375** |         |
|                   | (0.056) | (0.137) |         |
| Leisure content   | 0.650***| 0.965***|         |
|                   | (0.081) | (0.194) |         |
| **Image color attributes** |         |         |         |
| Color richness    | −1.075***| 0.349  |         |
|                   | (0.172) | (0.535) |         |
| **Moderate effect** |         |         |         |
| Household*color   | −0.151* |         |         |
|                   | (0.076) |         |         |
| Leisure*color     | −0.194‡ |         |         |
|                   | (0.109) |         |         |
| **Time and region** |         |         |         |
| month release     | 0.189***| 0.189***|         |
|                   | (0.009) | (0.009) |         |
| City GDP          | 0.000***| 0.000***|         |
|                   | (0.000) | (0.000) |         |
| **House features** |         |         |         |
| Price             | −0.001**| −0.001**|         |
|                   | (0.000) | (0.000) |         |
| Size              | −0.008***| −0.008***|         |
|                   | (0.002) | (0.002) |         |
| Rooms             | 0.119  | 0.121  |         |
|                   | (0.148) | (0.148) |         |
| LIVING rooms      | 0.658** | 0.658** |         |
|                   | (0.217) | (0.217) |         |
| Bathrooms         | −0.588***| −0.589***|         |
|                   | (0.170) | (0.170) |         |
| Kitchens          | 1.243***| 1.252***|         |
|                   | (0.324) | (0.324) |         |
| Balconies         | −0.066  | −0.075  |         |
|                   | (0.179) | (0.179) |         |
| _cons             | −2.603***| −4.928***|         |
|                   | (0.576) | (1.006) |         |
| R²                | 0.125  | 0.126  |         |
| (Adjusted R²)     | 0.124  | 0.125  |         |
| Obs               | 9183   | 9183   |         |

Standard errors are in parenthesis

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ‡ $p < 0.1$
and leisure products’ impact on tenant booking decision-making are negatively moderated by color richness ($\beta = -0.151$, $p < 0.05$ and $\beta = -0.194$, $p < 0.1$), indicating that the intention of tenants’ booking a house whose image displays much household goods or leisure products may be weakened if its image is too colorful. Hypothesis 4a is supported. According to previous results and discussion, the influence of image content on tenant satisfaction is not significant, so the relationship will not be moderated by color richness, thus hypothesis 4b is not supported.

Figure 7 summarized the main results of this research.

### 6 Conclusions and discussion

This article studied the relationship between house images and tenant booking decision-making and satisfaction on online short-term rental platform. We applied Computer Vision techniques to process images, quantifying the visual attributes of images, and applied Sentiment Analysis techniques for calculating review sentiment. Then we use OLS to study the relationship between image attributes such as color richness, household content, and leisure content and tenant booking decision-making and satisfaction.

We find that color richness is negatively correlated with both the tenant booking decision-making and satisfaction, and displaying more leisure products as well as household goods on house image will attract more tenants to book the house, but won’t make tenants more satisfied. The reason of the insignificance relationship between the image content and tenant satisfaction may be that the contents of the house images are relatively objective and will not differ a lot from what the house really has. So the satisfaction level of all booked house is generally similar and the offline experience will not change it a lot. We also find that
the influence of house image content, including household and leisure content, is negatively modified by house image color richness.

This research makes several theoretical contributions. This research applied the primacy effect to the research field of consumer decision-making, and identified the relationship between house images and tenant decision-making which includes tenant booking decision-making and tenant satisfaction. The findings illustrate tenants’ preference in choosing short-term rental houses using data of a famous short-term rental platform in China. Among the previous studies of home sharing, few of them focused on the detailed information of the house represented by images, such as colors and contents. However, we find that lower color richness and more contents shown in house images are connected with higher tenants booking and satisfaction. Our research fills the research gap of these detailed information and tenant purchase behavior in the field of home sharing. This research enriched the expansion of this consumer decision making literature and theory in home sharing.

There are also some practical suggestions for short-term rental platforms. According to the result of this research, lower color richness and more household and leisure contents is related to higher transaction in short-term rental platform. From the dataset we can see that color richness and contents of house images vary widely, which means some images of the houses may not be preferred by potential tenants. In order to attract more users and improve its efficiency, short-term rental platform can try to formulate the requirements and specifications of house images, or set up a professional team to take images of houses with higher content richness and lower color richness.

For landlords in short-term rental platform, they are suggested to choose the right decoration style. The interior colors should be as consistent as possible, and it is not appropriate to use high color contrast. More leisure products (e.g., plants and hanging pictures) and household goods (e.g., furniture and facilities) should be provided to meet tenants’ needs and thus enhance tenant’s purchase decision making. Landlords may also pay more attention to the house image on the platform. A good shooting angle is needed to show the facilities of the house as comprehensively as possible. Make the color of the house image more harmonious by shooting in the appropriate light and post-processing to avoid showing too strong color contrast. These approaches can help landlords attract more tenants.

This research also has some limitations. (1) The data we analyzed is from only one platform, so the generalizability of our research result is restricted. It will be better if we can simultaneously analyze data from several other platforms. (2) No booking data in analysis. Because the short-term rental platform does not show how many times a house had been booked historically, we cannot get the booking data which measures tenant booking decision-making best. Although previous studies supported the hypothesis that the number of reviews is a proxy for online sales, it may be affected by other factors such as tenant’s characteristics. So using the number of reviews to measure tenant booking decision-making may lead to some bias in our analysis. (3) The control variable price can change over time. However, we use the price of the houses of the date when we get the dataset as the price of the houses, that may lead to some estimation bias.
In the future, we will further explore how different dominant colors can be paired to benefit the home sharing transaction utilizing the house images. As is widely known, the breakout of COVID-19 has a great impact on home sharing. We will try to follow the development of home sharing platforms and compare the different impacts before and after the COVID-19 in future research.

Acknowledgements This study is financially supported by the National Natural Science Foundation of China (72272075, 71872086), and the Fundamental Research Funds for the Central Universities (Nanjing University Special Program for Middle and Long Term Outstanding Research in New Era Humanities and Social Sciences 14914220, and Nanjing University Special Program for Young Faculty in Interdisciplinary Humanities and Social Sciences, 14370115).

References
1. Needed, M. (2020). Airbnb by the Numbers: Usage, Demographics, and Revenue Growth. https://muchneeded.com/airbnb-statistics/#:~:text=Fast%20forward%20today%20and%20more%20at%20given%20time.
2. Ting, D. (2017). Airbnb Is Becoming an Even Bigger Threat to Hotels Says a New Report. https://skift.com/2017/01/04/airbnb-is-becoming-an-even-bigger-threat-to-hotels-says-a-new-report/.
3. Moriya, J. (2018). Visual mental imagery influences attentional guidance in a visual-search task. *Attention, Perception, & Psychophysics*, 80(5), 1127–1142. https://doi.org/10.3758/s13414-018-1520-0
4. Peck, J., & Childers, T. L. (2003). To have and to hold: The influence of haptic information on product judgments. *Journal of Marketing*, 67(2), 35–48. https://doi.org/10.1509/jmkg.67.2.35.18612
5. Yoo, J., & Kim, M. (2012). Online product presentation: The effect of product coordination and a model’s face. *Journal of Research in Interactive Marketing*. https://doi.org/10.1108/1750593121241378
6. Yoo, J., & Kim, M. (2014). The effects of online product presentation on consumer responses: A mental imagery perspective. *Journal of Business Research*, 67(11), 2464–2472. https://doi.org/10.1016/j.jbusres.2014.03.006
7. Zhang, S., Lee, D., Singh, P. V., & Srinivasan, K. (2021). What makes a good image? Airbnb demand analytics leveraging interpretable image features. *Management Science*. https://doi.org/10.1287/mnsc.2021.4175
8. Ter Huurne, M., Ronteltap, A., Corten, R., & Buskens, V. (2017). Antecedents of trust in the sharing economy: A systematic review. *Journal of Consumer Behaviour*, 16(6), 485–498. https://doi.org/10.1002/cb.1667
9. Zhang, L., Yan, Q., & Zhang, L. (2018). A computational framework for understanding antecedents of guests’ perceived trust towards hosts on Airbnb. *Decision Support Systems*, 115, 105–116. https://doi.org/10.1016/j.dss.2018.10.002
10. Zervas, G., Proserpio, D., & Byers, J. (2015). A first look at online reputation on Airbnb, where every stay is above average. *Where Every Stay Is Above Average*. https://doi.org/10.1007/s11002-020-09546-4
11. Thomas, M.-J., Wirtz, B. W., & Weyerer, J. C. (2019). Determinants of online review credibility and its impact on consumers’ purchase intention. *Journal of Electronic Commerce Research*, 20(1), 1.
12. Kim, R. Y. (2020). When does online review matter to consumers? The effect of product quality information cues. *Electronic Commerce Research*. https://doi.org/10.1007/s10660-020-09398-0
13. Orús, C., Gurrea, R., & Flavián, C. (2017). Facilitating imaginations through online product presentation videos: Effects on imagery fluency, product attitude and purchase intention. *Electronic Commerce Research*, 17(4), 661–700. https://doi.org/10.1007/s10660-016-9250-7
14. Ert, E., Fleischer, A., & Magen, N. (2016). Trust and reputation in the sharing economy: The role of personal photos in Airbnb. *Tourism management*, 55, 62–73. https://doi.org/10.1016/j.tourman.2016.01.013
15. Song, S. S., & Kim, M. (2012). Does more mean better? An examination of visual product presentation in e-retailing. *Journal of Electronic Commerce Research*, 13(4), 345–355.
16. Xu, X., Zeng, S., & He, Y. (2021). The impact of information disclosure on consumer purchase behavior on sharing economy platform Airbnb. *International Journal of Production Economics*, 231, 107846. https://doi.org/10.1016/j.ijpe.2020.107846

17. Ert, E., & Fleischer, A. (2020). What do Airbnb hosts reveal by posting photographs online and how does it affect their perceived trustworthiness? *Psychology & Marketing*, 37(5), 630–640. https://doi.org/10.1002/mar.21297

18. Lee, C. K. H. (2022). How guest-host interactions affect consumer experiences in the sharing economy: New evidence from a configurational analysis based on consumer reviews. *Decision Support Systems*, 152, 113634. https://doi.org/10.1016/j.dss.2021.113634

19. So, K. K. F., Xie, K. L., & Wu, J. (2019). Peer-to-peer accommodation services in the sharing economy: Effects of psychological distances on guest loyalty. *International Journal of Contemporary Hospitality Management*. https://doi.org/10.1108/IJCHM-09-2018-0730

20. Jiang, Z., & Benbasat, I. (2004). Virtual product experience: Effects of visual and functional control of products on perceived diagnosticity and flow in electronic shopping. *Journal of Management Information Systems*, 21(3), 111–147. https://doi.org/10.1080/07421222.2004.11045817

21. Zhang, S., Lee, D. D., Singh, P. V., & Srinivasan, K. (2017). How much is an image worth? Airbnb property demand estimation leveraging large scale image analytics. *Airbnb Property Demand Estimation Leveraging Large Scale Image Analytics*. https://doi.org/10.2139/ssrn.2976021

22. Chi, M., Pan, M., & Huang, R. (2021). Examining the direct and interaction effects of picture color cues and textual cues related to color on accommodation-sharing platform rental purchase. *International Journal of Hospitality Management*, 99, 103066. https://doi.org/10.1016/j.ijhm.2021.103066

23. So, H., & Oh, W. Picture Perfect: An image mining of advertising content and its effects on social targeting. In *International Conference on Information Systems (ICIS) 2018 PROCEEDINGS*, 2018

24. Pieters, R., Wedel, M., & Batra, R. (2010). The stopping power of advertising: Measures and effects of visual complexity. *Journal of Marketing*, 74(5), 48–60. https://doi.org/10.1509/jmkg.74.5.048

25. Singh, V., Bhattacherjee, A., Kalapapatu, J., Srivastava, U., & Fu, S. The effect of image choice on airbnb reservations: A combination of deep learning and econometric analysis. In *AMCIS 2018 PROCEEDINGS*, 2018

26. Zhang, G., Cui, R., Cheng, M., Zhang, Q., & Li, Z. (2020). A comparison of key attributes between peer-to-peer accommodations and hotels using online reviews. *Current Issues in Tourism*, 23(5), 530–537. https://doi.org/10.1080/13683500.2019.1575339

27. Wilson, A., Zeithaml, V., Bitner, M. J., & Gremler, D. (2012). *Services marketing: Integrating customer focus across the firm* (2nd European Edition ed.).

28. Murdoch, B. B., Jr. (1962). The serial position effect of free recall. *Journal of experimental psychology*, 64(5), 482. https://doi.org/10.1037/h0045106

29. Wexner, L. B. (1954). The degree to which colors (hues) are associated with mood-tones. *Journal of applied psychology*, 38(6), 432. https://doi.org/10.1037/h0062181

30. Murray, D. C., & Deabler, H. L. (1957). Colors and mood-tones. *Journal of applied psychology*, 41(5), 279. https://doi.org/10.1037/h0041425

31. Aaronson, B. S. (1970). Some affective stereotypes of color. *International Journal of Symbolics.*

32. Papachristos, E., Tselios, N., & Avouris, N. Inferring relations between color and emotional dimensions of a web site using Bayesian Networks. In *IFIP Conference on Human-Computer Interaction*, 2005 (pp. 1075–1078); Springer. doi: https://doi.org/10.1007/11555261_108

33. Alfakhri, D., Harness, D., Nicholson, J., & Harness, T. (2018). The role of aesthetics and design in hotelscape: A phenomenological investigation of cosmopolitan consumers. *Journal of Business Research*, 85, 523–531. https://doi.org/10.1016/j.jbusres.2017.10.031

34. Yildirim, K., Hidayetoglu, M. L., & Capanoglu, A. (2011). Effects of interior colors on mood and preference: Comparisons of two living rooms. *Perceptual and motor skills*, 112(2), 509–524. https://doi.org/10.2466/24.27.PMS.112.2.509-524

35. Mojsilovic, A., Kovacevic, J., Hu, J., Safranek, R. J., & Ganapathy, S. K. (2000). Matching and retrieval based on the vocabulary and grammar of color patterns. *IEEE transactions on image processing*, 9(1), 38–54. https://doi.org/10.1109/83.817597

36. Chen, J., Pappas, T. N., Mojsilovic, A., & Rogowicz, B. E. (2005). Adaptive perceptual color-texture image segmentation. *IEEE transactions on image processing*, 14(10), 1524–1536. https://doi.org/10.1109/TIP.2005.852204

37. Ou, L. C., & Luo, M. R. (2006). A colour harmony model for two-colour combinations. *Color Research & Application; Endorsed by Inter-Society Color Council, The Colour Group (Great Britain), Canadian Society for Color, Color Science Association of Japan, Dutch Society for the Study...
To see and then to believe: how image affect tenant…

38. Ou, L. C., Ronnier Luo, M., Sun, P. L., Hu, N. C., Chen, H. S., Guan, S. S., et al. (2012). A cross-cultural comparison of colour emotion for two-colour combinations. *Color Research & Application, 37*(1), 23–43. https://doi.org/10.1002/col.20648

39. Szabo, F., Bodrogi, P., & Schanda, J. (2010). Experimental modeling of colour harmony. *Color Research & Application: Endorsed by Inter-Society Color Council, The Colour Group (Great Britain), Canadian Society for Color, Color Science Association of Japan, Dutch Society for the Study of Color, The Swedish Colour Centre Foundation, Colour Society of Australia, Centre Français de la Couleur, 35*(1), 34–49. https://doi.org/10.1002/col.20558.

40. Schloss, K. B., & Palmer, S. E. (2011). Aesthetic response to color combinations: Preference, harmony, and similarity. *Attention, Perception, & Psychophysics, 73*(2), 551–571. https://doi.org/10.3758/s13414-010-0027-0

41. Judd, D. B., & Wyszecki, G. (1975). *Color in business, science, and industry* (3rd ed.). John Wiley & Sons.

42. Tse, D. K., & Wilton, P. C. (1988). Models of consumer satisfaction formation: An extension. *Journal of Marketing Research, 25*(2), 204–212. https://doi.org/10.1177/002224378802500209

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.