Visual Experience of Space: Relating Textual Descriptions of Perceived Atmosphere to Luminance Contrast Metrics

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This exploratory study investigates the quantifiable relationship between image properties and the aesthetic perception of indoor environments, focusing on luminance contrast, light, form, and material variations. A diverse image set of everyday spaces was curated, and a comprehensive list of atmosphere descriptors was developed from lighting literature. Using pixel value distribution analysis, images were classified by luminance contrast, and 24 participants evaluated 15 images using 54 Turkish atmosphere adjectives on a 5-point semantic differential scale. Principal Component Analysis (PCA) of the responses revealed three components based on 43 adjectives related to perceived atmosphere. Notably, the second component was significantly correlated with luminance contrast, indicating that variations in light, color, and materials—and the resulting changes in luminance contrast—can influence atmospheric perception. The first and third components captured atmospheric qualities beyond luminance contrast. These findings provide valuable insights into how image attributes, particularly luminance contrast, impact aesthetic evaluations of indoor environments, contributing to the broader understanding of atmospheric perception in built spaces.

CCS Concepts: • Applied computing → Computers in other domains; Personal computers and PC applications; Computer games; Arts and humanities; Architecture (buildings); • Computing methodologies → Computer graphics; Graphics systems and interfaces; Perception; Image manipulation; Image processing; Artificial intelligence; Natural language processing; Information extraction; • Human-centered computing → Human computer interaction (HCI); Interaction devices; Displays and imagers;

Additional Key Words and Phrases: Aesthetic evaluation, Built environment, Light and material variations, Luminance contrast, Perceived atmosphere, Principal component analysis

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1 Introduction

Recognized as an experienced phenomenon, the atmosphere enables instant reading of the environment with primary, objective, and unconscious acts. The perception of the atmosphere operates differently than object-oriented approaches, such as the Gestalt principles, figure-ground dispositions, and cognitive processes in states of consciousness [1]. In this study about the visually perceived atmosphere of a scene, the main aim is to understand its relationship to luminous conditions in the built environment.

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According to the literature, different qualities of light, the luminosity framework, and the lighting atmospheres are influenced by each other [2]. For example, three minutes of exposure to diverse light conditions elicited different impressions of an environment [3]. A series of atmosphere studies have shown that light can transform an environment's affective evaluation or perceived atmosphere between comfortable, tense, lively, or detached [4, 5]. The visual appearance of space was also influenced by light's brightness and luminance distribution attributes [6, 7]. Accordingly, light alters how we filter information from our surroundings to generate an overall image [8]. Herein, we hypothesize that the luminance contrast, as an integrated brightness and distribution attribute, may be used to determine how the atmosphere of that scene is perceived.

Images often represent designed spaces and simulate real environments [9]. Engelke et al. [10] compared the atmosphere and appearance of the light in the room and found photographs statistically represented the same lighting impression as in a real-world setting or physically based renderings for the studied experimental room. Kim and Mansfield [3] have found that the subjective assessments for appearance (brightness, color temperature, distribution) and high-order perceptions (pleasantness, interest, spaciousness, excitement, and complexity) showed no differences in the perception of the lighting and the impressions of the room between the real and virtual office environments. In another study, the validity of simulations presented through the computer monitor and video projector was also compared to a mock-up where the lighting attributes of brightness and contrast were consistent between different mediums [11]. Therefore, this study concentrates on whether or not there is a significant correlation between perceived atmosphere adjectives and the luminous contrast levels of selected images. Luminance contrast, or the variation in an object's brightness from its backdrop, is the fundamental foundation for achromatic vision. For the initial study, these images are achromatic to control and focus on the effect of luminance contrast and pixel brightness before introducing another variable, the chroma. Phenomena related to colored images such as the Helmholtz–Kohlrausch effect [12], when a color's strong saturation is interpreted as an aspect of its brightness or the variety of contrast measures in addition to brightness contrast, incorporating color tone, saturation, and cool/warm contrast measures [13] could be investigated once this primary relation is established.

A recent survey revealed that white, grey, and black are seen as colors regardless of the color knowledge level [14]. "Because we see and distinguish them" is one of the answers when people say that white, grey, and black are colors. "Because contrast differences can be observed and they can be named and differentiated." is another response for these colors and their distinct relation to contrast. These colors have also been incorporated into chroma reduction color strategies as the chroma-reduced colors with grey create subtle "shadow" color distinctions, and chroma-reduced colors with white create tints [15]. We also wanted to refine atmosphere descriptions related to luminance contrast before their intersection with colors since strong associations exist between colors and concepts or words [16]. By investigating the luminance contrast of achromatic images, the study will ensure the inclusive list of atmosphere adjectives is only the effects of contrast in a scene. Then these could be utilized in colored scenes concerning architecture, lighting, visualizations, presentations, perceived atmosphere, and such queries will enable us to communicate more precisely and design environments that match desired qualities such as atmospheres.

The findings of this study also contribute to the evaluation of scenes as perceived atmosphere adjectives derived from systematically collecting and eliminating descriptions in the lighting literature. The listed atmosphere adjectives are evaluated image by image to determine whether there is a significant relationship between atmospheric adjectives and luminous contrast groups. The method of this study is based on two main concepts: luminance contrast and perceived atmosphere. Before the methodology section, this research article will begin with the main concepts' terminology and literature review.

1.1 Luminance Contrast

In the image or display context, contrast is the difference in brightness within the same field of view [17]. The two main factors of any visual input related to contrast measures are brightness, the perceptual correlate of light intensity, and spatial frequency, and the rate at which stimulus changes in a defined area. In the theory of vision and perception, scenes are processed in terms of spatial frequencies [18]. The light intensity in stimulus can be represented as the spatial frequency, which is a characteristic of any periodic structure as a measure of how often sinusoidal components of the structure repeat per unit of distance [19]. According to Westheimer [20], "observers are unaware of the individual spatial frequency components since all elements are blended into one smooth representation." However, conveyed information varies with different spatial frequencies, as does the image's appearance. Depending on these variables, the measurement of luminance contrast could be approached differently. The photo metric measurement of contrast could provide the same or completely different results from how the contrast is perceived in different images.

In the context of visual input, the contrast calculation method could also be determined in line with the image's simple or complex properties. Compounded variations of spatial frequency, brightness, and distribution factors produce more complex natural images. Simple images, such as a periodic pattern, utilize Michelson contrast with maximum and minimum luminance [21]. Weber fraction is another contrast measure used for a target before a uniform background [22]. When these contrast measures are used with simple images, perceived contrast would be analogous to photo metric contrast results. However, when used in complex images, extreme points alter the contrast ratio and mislead the measures in these mentioned methods. Local or global measures are preferred for complex images to calculate the minimum and maximum values throughout the image. These techniques enable the perceiver to notice the less obvious information in the original image [23]. Local measures calculate the minimum and maximum values locally [24]. For example, enhancing local contrast exposes fine detail visibility of an image [24, 25]. **Root Mean Square (RMS)** contrast is a global contrast measure that is free from the variables of spatial frequency and spatial distribution of contrast [26]. Comparison of two images could be practiced with RMS contrast, yet the perceived contrast value could be different considering the effect of contrast sensitivity over these two variables. For example, the effects of dark regions were found to be more dominant than light areas for perceived contrast [27].

For complex images, local-band limited contrast is an alternative method between the perceived and measured physical contrast to overcome this deficiency [25]. Each spatial frequency band measures the local contrast separately, so the contrast variation across the image could be factored in with a system similar to human visual processing. Instead of measuring the perceived contrast of the spatial frequency components separately, Haun and Peli have also employed the contrast judgment of observers [27]. According to their results, participants tended to make contrast judgments by spatial luminance variance. Following this approach, "Spatial Luminance Contrast" was proposed as a method developed over local contrast measure and RMS Contrast to extract information [28]. This procedure calculates the luminance variation between neighboring pixels to analyze the contrast. Using a pyramid scheme, pixel luminance variation between neighboring pixels is calculated for different resolution levels of the same image. At each level, the luminance contrast of eight neighboring pixels around the central pixel is calculated to create a new pixel value, representing a new pixel of the lower resolution image. Then, these values are used again to define the following value for a level up in the resolution pyramid. Similar to global contrast measures, the overall contrast value of the same image is calculated for each resolution step, from high to low. In this way, this algorithm considers brightness, spatial frequency, and contrast for complex images.

In 2016, Rockcastle et al. applied Spatial Luminance Contrast to architectural renderings [29]. They found this combined metric, RAMMG (Equation (1)), as a possible predictor for visual interest with subjective ratings. For N number of levels:

$$RAMMG = \frac{1}{N} \sum_{l=1}^{N} \bar{c}_l, \tag{1}$$

where $\bar{c}_l$ is the mean contrast in the level l

$$\bar{c}_l = \frac{1}{WH} \sum_{i=1}^{W_l} \sum_{j=1}^{H_l} c_{i,j}. \tag{2}$$

The image resolution is halved in each subsequent level, where $W_l = W_{l-1}/2$ and $H_l = H_{l-1}/2$ are the width and height of the image at level l and $c_{i,j}$ is the contrast of each pixel calculated as:

$$c_{i,j} = \sum_{k \epsilon K_8} \alpha \left| p_{i,j} - p_k \right|, \tag{3}$$

where pixels p_k are the eight neighbouring pixels of $p_{i,j}$ and the weight α applied to each of the eight surrounding pixels k is

$$\alpha = \frac{1}{4 + 2\sqrt{2}} \begin{bmatrix} \frac{\sqrt{2}}{2} & 1 & \frac{\sqrt{2}}{2} \\ 1 & & 1 \\ \frac{\sqrt{2}}{2} & 1 & \frac{\sqrt{2}}{2} \end{bmatrix}. \tag{4}$$

Responding to various subjective evaluations, the fifth level of the resolution pyramid scheme was deemed consistent as the RAMMG5 metric. Therefore, this study uses this algorithm to compute the monitor luminance of pixel contrast for the experimental images which will be referred as luminance contrast in this manuscript. Since this work's main focus is luminance contrast and the algorithm was developed for achromatic image calculations, the color characteristics of images were not investigated.

1.2 Perceived Atmosphere

The second concept is the perceived atmosphere in the context of light. Different definitions of atmospheres and their terminology can be found in the literature about aesthetics or qualities of the environment. Rather than a lack of atmospheric expressions, there is no consensus about how to discriminate these expressions from the expressions of mood, emotion, and alike. This confusion also exists for the language of light [30]. The profuseness of light terminology can be traced in the literature for psychology, architecture, physics, graphics, and visualization over practical, perceptual, experiential, and aesthetic concerns. According to Pont, many descriptions in this pool of light terminology address material properties and could be related to how the appearance of materials is only visible in certain illumination conditions [2]. Studies about the atmosphere of light have analyzed the semantic structure of informal descriptions [31, 32]. Semantic descriptions, such as the atmospheric expressions, are vaguer than the lights' terminology, as observers can assess and infer additional attributes beyond optical associations [33].

In 2008, Vogels collected descriptive atmosphere terms to measure the experienced atmospheres. The developed atmosphere questionnaire assessed varying lighting conditions [4]. The act of translation poses problems such as emerging the same/similar meanings for different terms or missing possible atmosphere terms outside the list. These studies building up on this atmosphere questionnaire have used its translation by examining atmospheres' relation to light [34, 35]. As the first translation appears in Vogels' atmosphere adjectives, different English translations of Dutch adjectives can be found. For example, two different Dutch adjectives can be found in the English translations of "cozy" and "pleasant." Besides, the term "warm" was the same for both languages. Another protocol for a lexicon was systematically examining related literature and selectively filtering words compatible with its definitions and translations [36]. By directly translating and using previous atmosphere terms and lists, it is apparent that some will become meaningless in Turkish or might not include Turkish atmosphere descriptions in the questionnaire. Thus, as Vogels' study draws attention to culture as a factor that should be considered and studied further, each semantic study of light contributes to its lexicon.

These studies focused on the effects of uniformity and intensity of light for its effects on spatial impressions in real or controlled environments. By considering images as atmospheric scenes, the luminance contrast measure can incorporate varying light properties in more complex environments, such as daily scenes. The uniformity and intensity properties might provide an estimated contrast, whereas the luminance contrast algorithm (RAMMG5) is a combination of local and global measures, making it more suitable for complex scenes [29]. Additionally, the combined measure RAMMG5 was found to be a potential predictor of appearance with subjective ratings. These varying approaches for understanding light qualities were adapted to this study and will be elaborated in the methods following the same order.

2 Methods and Procedure

Two simultaneous preparations were held for this exploratory study on luminance contrast and perceived atmosphere in images. One of these was composing an image set to be observed as the atmosphere visuals. The other was preparing atmosphere adjectives to be rated in the questionnaire. Together, the experiment presented each image separately and collected atmosphere adjective ratings per image viewing.

2.1 Experiment Images

Image properties relating to its format were requisite of the RAMMG contrast measure. Images were taken with a Canon 60 D DSLR camera with an EF-S 18–135 mm f/3.5–5.6 Lens. All images shared the same size and were saved in the sRGB format. The main focus was providing a variety of light and space combinations in these images of the built environment. 155 images were taken, converted to greyscale, calibrated to experiment display, and categorized according to their RAMMG5 contrast values.

An essential feature of initial photographs was their content. Any connotations for trends and culture and the aesthetics of photographic framing were limited by capturing generic scenes from modern everyday life. No human figures were included while preserving a variety of daylight, artificial light, indoors and outdoors, different functions, sizes, and geometry of space and materials. The image pool consisted of photographs of galleries, a theatre hall, a cinema, a book store, a chocolate shop, a grocery store, shopping mall atrium, corridors, a pub, cafes, an apartment entrance, facades, a subway, an overpass, parks, a skate park, a car park, and a tribune. Concerning the atmosphere of the spaces, no further criteria were applied to preserve the diversity of built environments in the represented images.

The color attributes of these photographs were not examined further since this study primarily probes the luminance contrast of achromatic images. RGB channels of original images were converted to a greyscale layer, where the value of each pixel is the weighted sum of the corresponding pixels' red, green, and blue pixels contribution. Using Python programming software [37], the standard RGB to greyscale conversion formula was applied to all photographs [38].

$$Luminance = 0.2126 * R + 0.7152 * G + 0.0722 * B.$$

These exported images were then calibrated to the experiment display, where each pixel value was ensured to be displayed as their exact luminance values. Concerning the non-linear nature of contrast and brightness correlation, we have attempted to equalize the mean luminance of the experimental images. After using the Shine Toolbox for MATLAB software [39], Luminance Match, the mean luminance was limited to a range; however, this drastically reduced the variety of contrast results. The change has also presented visual problems, such as lost details in dark areas, faded tones, and sharpness (Figure 1). Therefore, the brightness level of the original image set was conserved for this experiment. An alternative precaution was applying a neutral grey image background and a blank neutral grey adaptation screen amongst images.

Following the conversion and the calibration phases, the RAMMG5 contrast values of all images were calculated. Due to the relative values subject to the display properties, luminance contrast results or histograms of calibrated images were not featured here. Instead, these results were grouped as outliers and five categories in between. This way, these luminance contrast categories could be referred to in future studies' varying displays and image

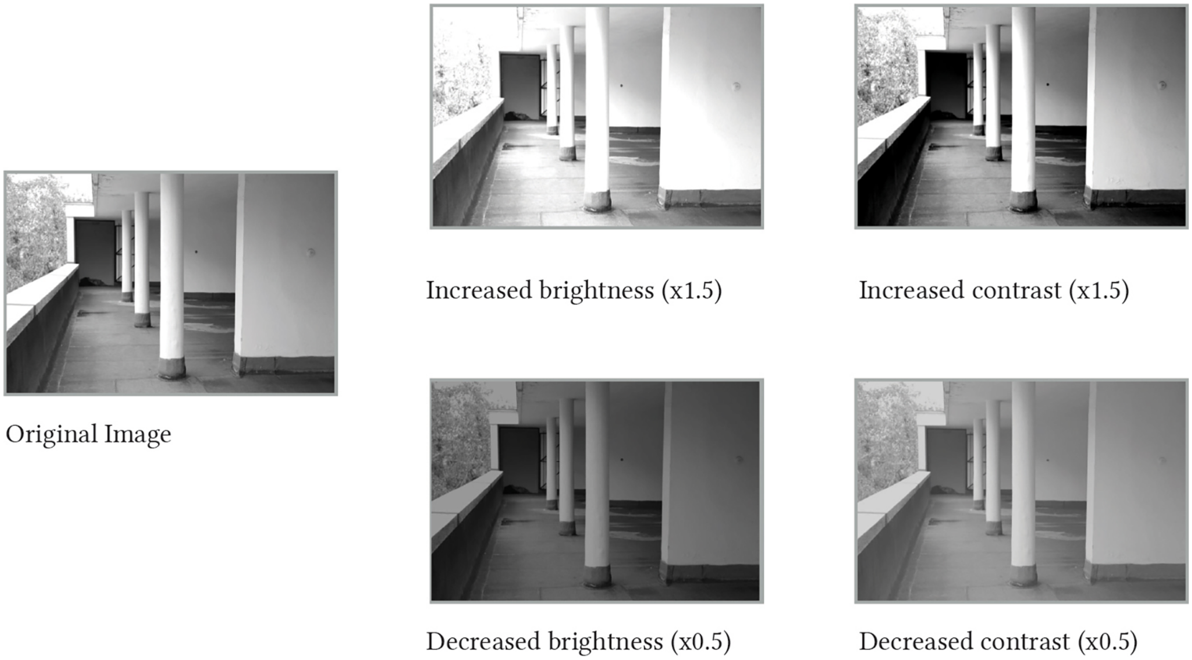


Fig. 1. An image example with increased and decreased image brightness and luminance contrast variations.

sets. Images falling into the outliers were not evaluated further for two main reasons. Very low contrast levels were especially close to one upper group and fell in that range due to camera settings such as the diaphragm or shutter speeds. In comparison, images with very high contrast levels had sky components in the frame that altered the remaining areas with their bright values. For instance, the highest RAMMG5 results couldn't be found in the image pool when daylight or sky components were not visible. The remaining five contrast categories of RAMMG5 measure, from low to high, have formed the image pool. The distribution of images within each category was not even; hence, the experimental image count had to be effectively decreased to 15 experimental images. Three images from each contrast category were selected, where considerations for this selection were compatibility with atmosphere adjectives, inclusively representing light, material, and spatial variations within the experimental set (Figure 2).

A limitation of this approach is its reliance on a set of 15 grayscale images, selected from an initial pool of 155 photographs captured with a Canon 60 D DSLR camera. Images were converted to grayscale and categorized by RAMMG5 contrast values to ensure a range of light and space combinations (Figure 3). While this method allowed for precise calibration and evaluation of luminance contrast, it limited the diversity of visual stimuli, excluding color and broader environmental variability, which might restrict the generalizability of the findings.

The image count and sample size were also bound to the rated atmosphere adjectives. A recommendation for **Principal Component Analysis (PCA)** is a minimum subject-to-item ratio of at least 5:1 [40, 41]. It is beneficial to keep the image variety; however, the duration of the experiment was also a constraint. In conclusion, 15 images, three from each contrast category, were specified for their content and RAMMG5 results. Two additional images were specified from this pool and included at the beginning of the questionnaire to illustrate how contrast levels alter images (Figure 4).

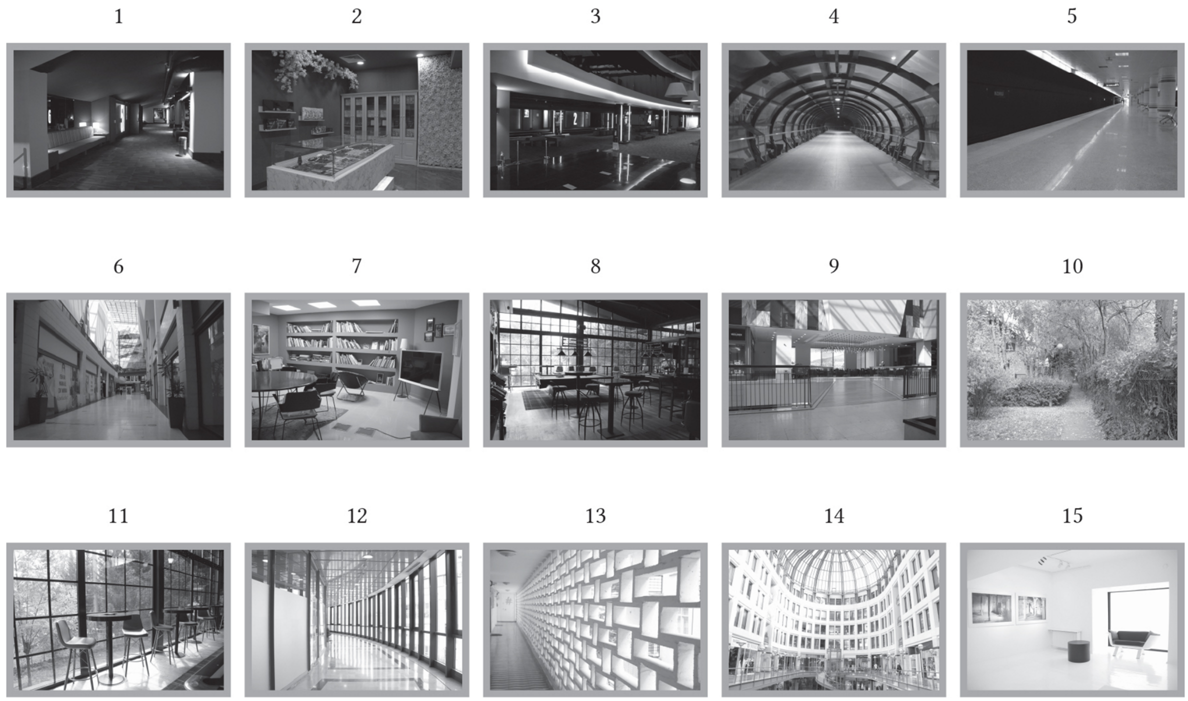


Fig. 2. Experiment images from low to high luminance contrast categories.

2.2 Rating Atmosphere

The following stages were completed to recompile Turkish words for visually perceived atmosphere experiences related to light. Adjectives from previous studies about impressions of light, light, and atmosphere were gathered and then grouped into Vogels' three categories which were found by studying light and atmosphere descriptions of participants [5]. The adjective categories were related to the emotion or mood evoked by the environment, related to the atmosphere of the environment, and terms that give a more or less objective description of the environment. The current study's remaining adjectives that did not fit any group were eliminated, these were evaluating the design style, stating opinions, adjectives related to other senses (hearing/taste/touch, etc.), descriptions of light sources, and material properties.

The adjectives related to the atmosphere of the environment were translated into Turkish. The adjectives with the same meanings and those that became meaningless after translation were eliminated. The validity of the remaining adjectives as atmospheric terms was controlled by placing them in the following sentence. "This space/place is _______." The adjectives that do not fit in this sentence were removed. The remaining words were grouped according to the similarity of their meanings by cross-referencing their appearance in the dictionary definitions. Finally, selected adjectives were controlled, considering the context of experimental images. The Dutch and Turkish phrases found in the literature from Vogels [5] and Kumsar [32] were retraced to check if the final list is exhaustive with these findings.

In summary, the first stage gathered 595 terms related to described qualities of light as impressions and atmosphere. 247 terms were repetitions, and 109 terms were removed as they wouldn't fit into the three categories of mood, atmosphere, and objective descriptions. The remaining 239 terms were located in these categories: Group 1 (33 words for mood), Group 2 (135 words for atmosphere), and Group 3 (71 words for objective descriptions). Translation of Group 2 included Turkish synonyms and returned 223 adjectives deriving from 135 words. These

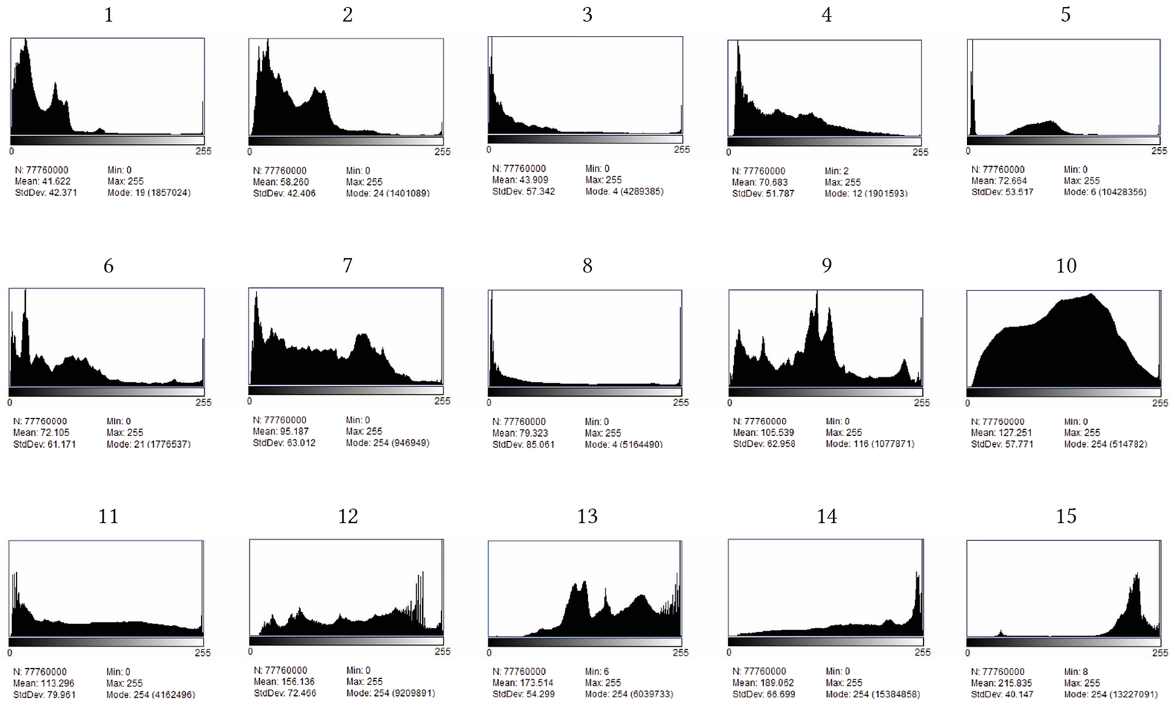


Fig. 3. Histograms of 15 experiment images.

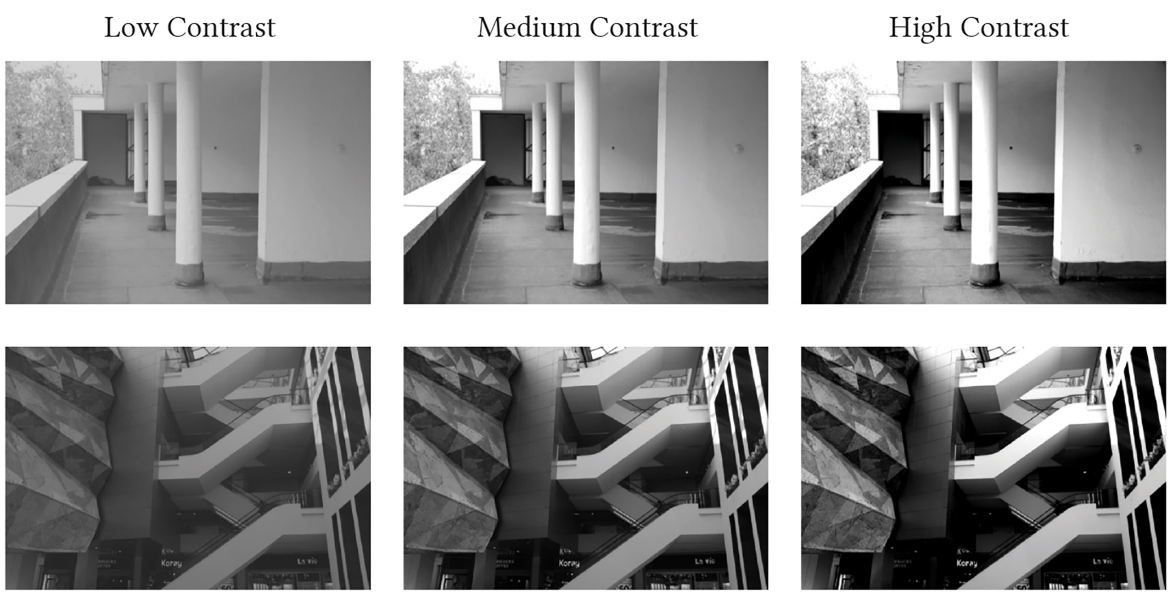


Fig. 4. Two example images used to illustrate low, medium, and high contrast variations to the participants.

Table 1. The List of 54 Atmosphere Adjectives

Ambiguous	Artificial	Balanced	Blurry
Bright	Comfortable	Clear	Confined
Cool	Dark	Deep	Depressing
Detailed	Different	Dim	Divergent
Dull	Dynamic	Exciting	Faint
Formal	Gloomy	Heavy	Impressive
Insincere	Interesting	Intimate	Inviting
Lifeless	Limpid	Lively	Messy
Mysterious	Narrow	Natural	Ordinary
Plain	Pleasing	Proximate	Remote
Romantic	Spacious	Somber	Shallow
Roomy	Still	Strict	Subdued
Transparent	Unappealing	Uneven	Unique
Uncomfortable			

were placed in the sentence "This space/place is _______." to check their validity in defining atmospheres. 169 adjectives were eliminated for not fitting this sentence or being synonyms. Table 1 presents the specified 54 Turkish adjective translations, which will be rated on a 5-point Likert scale in the questionnaire.

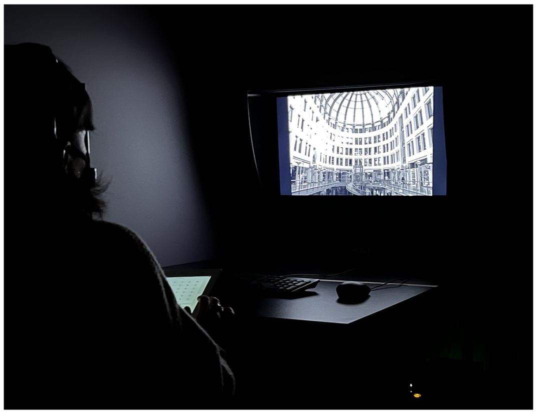
2.3 Procedure

The experiment was held in a controlled experiment room at the Aysel Sabuncu Brain Research Center, Bilkent University, Turkey. All the subjects have provided informed consent and the experiment ethical approval was obtained from Bilkent University Ethics Committee with No2022_02_22_01. Like most concepts related to vision, contrast sensitivity is prone to age-related change over time. Therefore, university students with no visual impairments and native Turkish speakers were asked to complete this experiment.

A display screen (NEC 30-inch Widescreen LED Backlit LCD Wide Gamut Desktop Monitor) and a remote tablet computer (iPad 2012 with 9.7-inch Retina display) were the only light sources in the experiment room. The display supports 2,560 × 1,600 resolution, 1,000:1 contrast ratio, 340 cd/m^2 maximum brightness, and the experimental images were calibrated with this monitor's LUT values. Participants were seated 75 cm from the monitor, and their responses were collected via the tablet located next to the participants' seats. The tablet was on greyscale mode and had the lowest brightness to display the questionnaire which collected participant responses from 1(strongly disagree) to 5(strongly agree) per adjective (Figure 5). There were no time restrictions on the display duration of the images. Each participant was asked to rate 54 atmosphere adjectives separately while viewing a single image. This procedure was repeated for each of the 15 images. Following a semi-Latin square design, a rotation of image order was achieved between the measured luminance contrast groups. Three groups of six participants viewed the same images in three different orders.

3 Results

At Bilkent University, 24 Turkish students participated in the experiment. Their average age was 23, and they were between 19 and 35. The students majored in interior architecture and environmental design (15), architecture (4), urban design and landscape architecture (2), and communication and design (3). The experiment lasted between 14 to 47 minutes, averaging 21 minutes. With SPSS Statistics software [42], PCA, Kruskal Wallis, and Spearman's correlation tests were performed to determine the atmosphere components and their relation to the luminance contrast of images, respectively.



For each word below, indicate to what extent this word applies to the atmosphere of the space in viewed image, on a scale from "strongly disagree" to "strongly agree" . *

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Remote	○	○	○	○	○
Plain	○	○	○	○	○
Romantic	○	○	○	○	○
Ordinary	○	○	○	○	○
Balanced	○	○	○	○	○
Absorbing	○	○	○	○	○

Fig. 5. (Left) The experiment room with image display screen and a separate tablet used by one of the participants. (Right) Questionnaire format sample, which included 54 adjectives for each image.

3.1 Atmosphere Components

Spearman's rho correlation coefficient values for atmospheric adjectives varied from −0.60 to 0.66, with terms having positive or negative correlations showing that participants used these terms similarly. Both Kaiser–Meyer–Olkin's measure (0.769) and Bartlett's test with a significance of 0.000 ($p < 0.005$) indicate that the 100% variance of the data is sufficient to carry out a PCA.

The question of how many components will be extracted is a determinant in interpreting PCA results. There are two typical approaches in the literature: selecting all components with eigenvalues greater than one and selecting elements that stand out against the subsequent components in the scree plot [41]. The Kaiser rule ignores components with eigenvalues less than 1.0 because they represent the information accounted for by an average single item [43]. However, following only this criterion is not recommended as it tends to extract many components [44]. After the Varimax rotation, there were 15 atmospheric components with the first technique. With the second approach, the scree plot showed three main components. The first two components explain 33.6% of the data, whereas the total variance increases to 44.3% when the third component is included. The remaining eigenvalues decreased drastically from 2, so the first three components were deemed adequate for describing the main atmosphere dimensions. According to the literature [45, 46], the explained variance is lower in humanities, around 50%, than in natural sciences, around 95%. Therefore, with the combination and consideration of these approaches, the total of 44.3% variance explained over three components was the accepted result. In these components, 11 adjectives were removed from the list as they fell below the 0.4 component loading threshold. The remaining 43 adjectives were grouped accordingly in Table 2.

3.2 Images and Atmosphere Components

According to the Shapiro–Wilks normality test, the rated adjectives were not normally distributed. The dataset was studied considering five contrast categories of experiment images. In this case, the pairwise comparison of these images and their adjusted significance levels helps us find which images were significantly different in their relationship to atmosphere components. Kruskal–Wallis Test results displayed asymptotic significance between images and Components 1 and 2 separately ($p = 0.000$ at 0.05 significance level). Each line in Figure 6 tests the null hypothesis that the two images' component distributions are the same, and the yellow lines indicate asymptotic significance in the two images. Low to medium contrast image numbered 4, medium contrast image numbered 7, and high contrast image numbered 15 were found in both component plots.

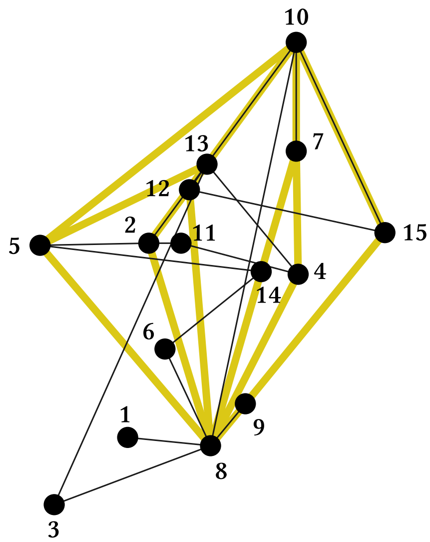
Table 2. Atmosphere Components and Related Adjectives Loadings of PCA Results

Component 1			
Component Loading	Atmosphere Adjective	Component Loading	Atmosphere Adjective
−0.74	Impressive	0.53	Uneven
−0.69	Spacious	0.53	Faint
−0.64	Inviting	0.59	Messy
−0.64	Natural	0.63	Cool
−0.60	Open	0.66	Dull
−0.56	Different	0.69	Artificial
−0.53	Clear	0.75	Confined
0.44	Heavy	0.76	Insincere
0.45	Dim		
Component 2			
Component Loading	Atmosphere Adjective	Component Loading	Atmosphere Adjective
−0.75	Lively	0.59	Blurry
−0.64	Bright	0.62	Uncomfortable
−0.58	Exciting	0.64	Subdued
−0.57	Roomy	0.68	Narrow
−0.54	Dynamic	0.73	Lifeless
−0.50	Transparent	0.77	Gloomy
−0.47	Intimate	0.78	Depressing
0.54	Dark		
Component 3			
Component Loading	Atmosphere Adjective	Component Loading	Atmosphere Adjective
−0.80	Unappealing	0.49	Romantic
−0.80	Ordinary	0.65	Deep
−0.70	Superficial	0.75	Interesting
−0.64	Formal	0.75	Unique
0.46	Detailed	0.77	Pleasing
0.47	Comfortable		

The asymptomatic images from Components 1 and 2 were analyzed further with Spearman's correlation to confirm a correlation to luminance contrast. For Component 1, 2, 4, 7, 8, 10, 12, 15 numbered images present no correlation to luminance contrast (coefficient value = 0.178 and p = 0.188 at the 0.01 level). However, Component 2, 1, 4, 7, 9, 11, 15 numbered images, had a correlation coefficient value 0.603 (p = 0.000) at the 0.01 level(2-tailed). The luminance contrast of these images was correlated to Component 2 adjectives (Figure 7).

Apart from the components, all 54 adjectives were separately analyzed with Spearman's correlation. These results were consistent with prior analyses, as 11 removed adjectives and those in Components 1 and 3 were not significantly correlated to image contrast levels. In other words, Component 2 consists of atmosphere descriptions that could be attained by setting luminance contrast on varying levels. Components 1 and 3 represent perceived atmosphere descriptions for light, bound to concepts other than luminance contrast.

1	60.38
2	34.38
3	56.00
4	30.75
5	22.38
6	58.25
7	47.88
8	110.00
9	61.75
10	98.50
11	81.62
12	38.62
13	85.88
14	78.25
15	41.88



1	24.62
2	38.62
3	42.50
4	21.25
5	38.12
6	71.25
7	87.38
8	52.75
9	90.88
10	81.62
11	90.62
12	70.75
13	43.25
14	64.50
15	88.38

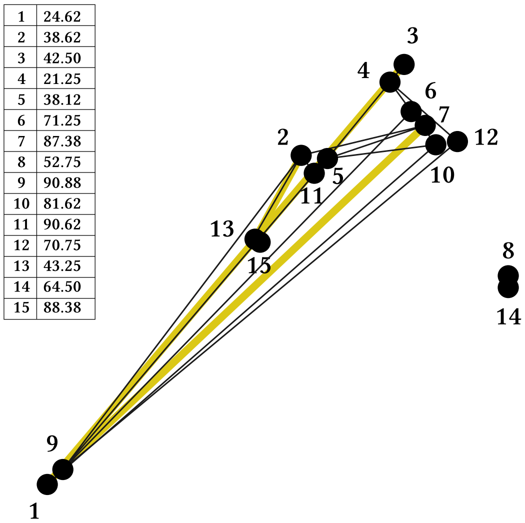


Fig. 6. (Left) Component 1 and (Right) Component 2 distributions with image pairs. Each node shows the sample average rank for the related component to image number. Asymptotic significances are marked with yellow lines.

Fig. 7. Asymptotic images are found in components 1 and 2. The luminance contrast of these images (Left Group) was correlated to component 2 adjectives. The luminance contrast of these images (Right Group) was not correlated to component 1 adjectives.

Table 3. Atmosphere Adjectives and Luminance Contrast Categories

Luminance Contrast Categories	Image	Atmosphere Adjective[a]			
Low	1, 2, 3	Artificial	Confined	Dark	Dynamic
		Gloomy	Narrow	Dim	
Low to Medium	4, 5, 6	Artificial	Uncomfortable	Dark	Cool
		Gloomy	Depressing	Dim	Lifeless
Medium	7, 8, 9	Roomy	Inviting	Clear	Natural
Medium to High	10, 11, 12	Lively	Impressive	Bright	Intimate
		Dynamic	Transparent	Clear	Natural
		Spacious	Inviting		
High	13, 14, 15	Bright	Lively	Clear	Roomy

[a]These atmosphere adjective means were above 4.00 and participants rated these as Strongly Agree and Agree.

3.3 Atmosphere Adjectives

Describing positive and negatively associated adjectives is an alternative way to interpret these relations in terms of luminance contrast. Table 2 was created by grouping each adjective with the highest absolute loading on one component above the 0.4 value. Table 3 presents the means of atmosphere rating distributions over each image to study participant responses from 1(strongly disagree) to 5(strongly agree) per adjective.

Upon an initial inspection, the adjectives' meanings do not add up as they are neither bipolar nor similar descriptions. However, participants agreed upon certain adjectives in Table 3 for images in specific luminance contrast categories. For example, the artificial adjective was found in lower contrast categories and the natural adjective was found in medium contrast images by comparison. Negatively associated descriptions such as confined, dark, dim, narrow, lifeless, or uncomfortable were associated with low-contrast images, except the dynamic adjective. Images with medium to high contrast were also described as dynamic, whereas other positively associated adjectives were bright, inviting, impressive, spacious, and lively.

4 Discussion

This exploratory study investigated luminance contrast and the perceived atmosphere relation as observed in images. The RAMMG5 algorithm [29] was used to compute the luminance contrast of the achromatic experimental images. From an initial pool of 155 images, we selected 15 grayscale images representing five contrast categories, as determined by the RAMMG5 metric. This approach enabled us to examine the relationship under conditions that mirror the dynamic range observed in everyday settings. Although the images were presented in grayscale to focus on luminance factors, the contrast measurements remain representative of natural environmental variations. The built environment scenes were rated on an extensive list of atmosphere adjectives which was generated based on the literature on atmosphere and lighting attributes. The results were analyzed in several manners; first, a PCA was used for dimensionality reduction, and then the extracted components were studied for their relation to the luminance contrast of images. Only the second component was found to be related to luminance contrast, and the adjectives belonging to this component will be detailed in this section. The other components, first and third, were not related to luminance contrast; however, the adjectives indicate other attributes of light and atmosphere beyond the extend of contrast. These won't be discussed here yet could benefit from future research on the topic of perceived atmosphere.

Compared to Vogels' study [5], more terms were tested in this research; hence, more factors have emerged. This might be due to the different applications of environments in images or the mere use of images. The analyses revealed that some of the atmosphere adjectives were compatible with Vogels' initial studies, in which four underlying atmosphere dimensions were tenseness, coziness, liveliness, and detachment. For example, "Exciting"

Fig. 8. Lowest luminance contrast image (Left) and highest luminance contrast image (Right) from the experiment.

and "Lively" are found under the liveliness dimension, and these atmosphere descriptions were correlated to luminance contrast in this study. The "Intimate" description, also grouped under coziness, corresponds to images with luminance contrast category medium to high. These exclusive adjectives could be reviewed for incidence in different languages and procedures in the atmosphere lexicons.

According to the previous findings, different brightness and perceived uniformity combinations may indicate the same atmosphere dimensions [4]. These two light attributes were also necessary to characterize the perception of light in an environment, where the first corresponds to the perceived intensity of the light and the latter to the perceived uniformity [47]. The current study found that the lively adjective was correlated to luminance contrast and corresponded to images with medium to high contrast categories. This luminance contrast range could be broken down to prior studies' findings of increasing brightness or altering perceived uniformity as both could result with the perceived atmosphere liveliness. For example, perceived uniformity was found to change greatly without influencing the perceived liveliness of the environment, and luminance contrast measure might be more suitable to address the fine tuning in such cases. In other words, the luminance contrast algorithm's inherent brightness and spatial frequency properties could be claimed as the counterparts when observed in images.

Similarly, the preliminary work about the identified influences of lit environments presents perceptual factors of an impression as "evaluative impression, perceptual clarity, spatial complexity, spaciousness, and formality" [6]. Amongst these, perceptual clarity and spaciousness were explained as physical variations in measured brightness, the dim-bright, and how they influenced wall brightness, uniform-non-uniform dimensions, on the latter. Component 2 adjectives such as bright, dark, roomy, narrow, gloomy, lively, or dynamic could be related to these physical variations correlated to the luminance contrast measure. Different light modes also affect the luminous contrast over the brightness and spatial frequency concepts. Such as luminance per pixel, similar to measured brightness, and area distribution of these pixel values, namely the influence on wall brightness.

The area distribution of contrast values in the images visibly affected the luminance contrast results and associated atmosphere impressions. For example, in Image 15, the light areas can present very large luminant areas for the high luminance contrast values. Thus, the high percentage of these areas overrides the negative impressions from the small percentage of dark areas, causing the high contrast in the first place. Bright, lively, clear, and roomy were the preferred adjectives for this scene. For the low-contrast Image 1, the large dark areas lack luminance contribution to the overall scene, resulting in low luminance contrast results even though local higher contrast levels could be found on several spots (Figure 8). Dark, dim, narrow, and gloomy were the agreed adjectives for this scene.

For the atmosphere adjectives, selecting an umbrella term for these components might be convenient; however, spotting the differences among the three adjective groups is also essential. Defined as the effect, the atmosphere can be the interactions between subject and object and subject to subject [48]. A potential relationship between a space's perceived atmosphere and the human (short-term) mood was found in earlier studies where the human mood was self-rated after around 20 minutes of exposure to each light condition [3]. This study separated the adjectives that were not descriptive of physical properties but based on the latter interactions. For example, "beautiful," "special," and "boring" adjectives were found to not correlate to luminance contrast, nor were they listed in the list of components. Following this definition, it could also be claimed that the adjectives belonging to the other components describe the combination of luminous and spatial properties of that space's atmosphere observed by the participants. Lastly, a few adjectives are important to mention for their meanings. In Turkish, Uzak (remote) and Yakın (proximate) are descriptive adjectives for location. Even though they respond to the depth dimension, they are not commonly used to describe the properties of space. In comparison, Basık/Ferah (Depressing/Spacious) and Açık/Kapalı (Open/Confined) adjectives correspond to the height of a space. Geniş/Dar (Roomy/Narrow) adjectives related to the width of space were found to be correlated to luminance contrast. Secondly, the meanings of the eliminated adjectives are very similar to some adjectives found under the components. For example, Ciddi (Strict) is one of the thesaurus entries for Resmi (Formal). For this reason, the eleven adjectives from 54 rated atmosphere adjectives could also be argued as similar adjectives that were misinterpreted or confusing for participants.

One limitation of this study is the use of **Low Dynamic Range (LDR)** images, which may have affected the accuracy of contrast measurements. Although the RAMMG5 metric was originally developed using **High Dynamic Range (HDR)** images, this study relied on single-exposure LDR images. Consequently, high luminance values in some scenes may have been clipped, potentially impacting contrast evaluations, particularly in areas with extreme lighting. Moreover, while the statistical results indicate perceptual responses to the displayed images, the study does not assert that the measured contrast ratios exactly replicate those of the real-world environments from which the images were captured, nor that the altered images directly correspond to any specific natural conditions. Rather, this exploratory investigation focuses on examining how variations in image contrast relate to perceived atmosphere across a diverse range of built environments—from outdoor areas to indoor spaces with artificial lighting. Future research could address these issues by incorporating HDR photography and contrast-preserving tone mapping operators for more precise contrast evaluations, as well as simulation-based approaches to better align image-based measurements with real-world conditions such as varying sky conditions or sun positions. Achromatic images and display properties could be other limitations of this study; however, image processing might be a more suitable alternative to investigate the impact of light on atmospheric perception beyond the scope of our interventions in real settings.

5 Conclusion

Light is one of the primary factors that create an atmosphere in the environment [49]; however, it cannot be studied exclusively from space and the surfaces with various materials in the surroundings. This study focuses on visually perceived atmospheres over the luminance contrast measure of achromatic images from built environments. The findings present extended effects of a luminous environment for the overall atmosphere of a scene. The PCA results specified 43-atmosphere adjectives as three components. Component 2 was identified as luminance contrast, and the adjectives in this component were correlated to image contrast levels. Thus, Component 2 comprises descriptions of the atmosphere that may be created by adjusting the measured luminance contrast of that scene (Table 4).

Components 1 and 3, on the other hand, are descriptions of the perceived atmosphere of light tied to notions other than luminance contrast. Three images from each of the five contrast categories were chosen (excluding outliers) based on their compatibility with the atmosphere adjectives and their representation of diverse light, material, and spatial variations. This rigorous selection process enabled a controlled evaluation of luminance contrast and pixel brightness effects on atmosphere perception, yet it also meant that the study focused exclusively

Table 4. Atmosphere Adjectives Correlating to Luminance Contrast

Bright	Blurry	Dark	Depressing
Dynamic	Exciting	Gloomy	Intimate
Lifeless	Lively	Narrow	Roomy
Subdued	Transparent	Uncomfortable	

on achromatic representations. The deliberate use of grayscale images was intended to isolate the influence of light and contrast, minimizing the potential confounding effects of color variations. Although color is a crucial factor in aesthetic perception—as evidenced by effects such as the Helmholtz–Kohlrausch phenomenon—its exclusion was intended to provide a controlled setting for exploring specific image variables.

Consequently, while the perceptual responses captured in our controlled laboratory setup offer valuable insights, they may not fully reflect the complexity of real-world visual experiences—where factors such as ambient lighting, spatial context, temporal variations, and color contribute significantly. It is important to note that our findings are particularly applicable to environments like screen displays, virtual settings, or computer-based applications, where the simplified visual conditions are inherent. Future research could extend these insights by incorporating a larger and more varied image set, employing advanced imaging techniques such as HDR photography, and including color information to more closely approximate natural conditions and further elucidate the multidimensional nature of atmosphere experience.

A more controlled study of brightness and luminance contrast is required to better understand the second component. It would be interesting to compare the achromatic image atmosphere rating results to the new chromatic scene results. The inclusive list of Turkish atmosphere adjectives and its intersection with prior studies also provides a base for ensuing atmosphere studies related to felt spaces. These descriptions could also be used as an atmosphere lexicon between the occupants and designers. Overall, a definable and countable link between image (in this study being defined as luminance contrast) and textual descriptions (in this study being defined as perceived atmosphere) would help both in creating relevant images and corresponding to images not only by traditional means but also through digital programming or artificial intelligence.

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References

[1] Gernot Böhme. 1993. Atmosphere as the fundamental concept of a new aesthetics. *Thesis Eleven* 36, 1 (1993), 113–126. DOI: https://doi.org/10.1177/072551369303600107
[2] Sylvia C. Pont. 2019. Light: Toward a transdisciplinary science of appearance and atmosphere. *Annual Review of Vision Science* 5 (2019), 1–25. DOI: https://doi.org/10.1146/annurev-vision-091718-014934
[3] Dong H. Kim and Kevin Mansfield. 2021. Creating positive atmosphere and emotion in an office-like environment: A methodology for the lit environment. *Building and Environment* 194 (2021), 107686–107686. DOI: https://doi.org/10.1016/j.buildenv.2021.107686
[4] Mariska Stokkermans, Ingrid Vogels, Yvonne De Kort, and Ingrid Heynderickx. 2018. A comparison of methodologies to investigate the influence of light on the atmosphere of a space. *LEUKOS* 14, 3 (2018), 167–191. DOI: https://doi.org/10.1080/15502724.2017.1385399
[5] Ingrid Vogels. 2008. Atmosphere metrics: Development of a tool to quantify experienced atmosphere. In *Probing Experience from Assessment of User Emotions and Behaviour to Development of Products*. E. Law and E. Van den Hoven (Eds.), Springer, Dordrecht, Netherlands.
[6] John E. Flynn, Terry J. Spencer, Osyp Martyniuk, and Clyde Hendrick. 1979. A guide to methodology procedures for measuring subjective impressions in lighting. *Journal of the Illuminating Engineering Society* 8, 2 (1979), 95–110. DOI: https://doi.org/10.1080/00994480.1979.10748577
[7] Jennifer A. Veitch and Guy R. Newsham. 1998. Determinants of lighting quality I: State of the science. *LEUKOS* 27, 1 (1998), 92–106. DOI: https://doi.org/:10.1080/00994480.1998.10748215

[8] Yvonne A. W. Kort. 2019. Tutorial: Theoretical considerations when planning research on human factors in lighting. *LEUKOS* 15, 2–3 (2019), 85–96. DOI: https://doi.org/10.1080/15502724.2018.1558065

[9] John E. Flynn, Terry J. Spencer, Osyp Martyniuk, and Clyde Hendrick. 1977. Procedures for investigating the effect of light on impression: Simulation of a real space by slides. *Environment and Behavior* 9, 4 (1977), 491–510. DOI: https://doi.org/10.1177/00139165779400330

[10] Ulrich Engelke, Mariska Stokkermans, and Michael J. Murdoch. 2013. *Visualizing lighting with images: Converging between the predictive value of renderings and photographs*. *HVEI* 18 (2013), 51–510. DOI: https://doi.org/10.1117/12.2008465

[11] Thomas Schielke. 2016. Validity of simulations for lighting and brand image evaluation. *Lighting Research & Technology* 48, 4 (2016), 473–490. DOI: https://doi.org/10.1177/1477153515589116

[12] Thanh H. Phung, Rik M. Spieringhs, Kevin A. G. Smet, Frederic B. Leloup, and Peter Hanselaer. 2022. Towards an image-based brightness model for self-luminous stimuli. *Optics Express* 30, 6 (2022), 9035–9052. DOI: https://doi.org/10.1364/OE.451265

[13] Shuang Wang, Wei Jiang, Yanan Su, and Jingyu Liu. 2020. Human perceptual responses to multiple colors: A study of multicolor perceptual features modeling. *Color Research and Application* 45, 4 (2020), 728–742.

[14] Jose L. Caivano. 2022. Black, white, and grays: Are they colors, absence of color or the sum of all colors? *Color Research & Application* 47, 2 (2022), 252–270. DOI: https://doi.org/10.1002/col.22727

[15] Edith A. Feisner. 2000. *Colour: How to Use Colour in Art and Design*. Laurence King, London, UK.

[16] Yun Chen, Jie Yang, Qianqian Pan, Marjan Vazirian, and Stephen Westland. 2020. A method for exploring word-colour associations. *Color Research & Application* 45, 1 (2020), 85–94. DOI: https://doi.org/10.1002/col.22434

[17] Wolfgand Einhäuser and Peter König. 2003. Does luminance-contrast contribute to a saliency map for overt visual attention? *The European Journal of Neuroscience* 17, 5 (2003), 1089–1097. DOI: https://doi.org/10.1046/j.1460-9568.2003.02508.x

[18] Louise Kauffmann, Stephen Ramanoël, and Carole Peyrin. 2014. The neural bases of spatial frequency processing during scene perception. *Frontiers in Integrative Neuroscience* 8 (2014), 37. DOI: https://doi.org/10.3389/fnint.2014.00037

[19] Robert Sekuler and Randolp Blake. 2002. *Perception*. McGraw-Hill, New York, NY, USA.

[20] Gerald Westheimer. 2001. The Fourier theory of vision. *Perception* 30, 5 (2001), 531–541. DOI: https://doi.org/10.1068/p3193

[21] Axlbert A. Michelson. 1927. *Studies in Optics*. University of Chicago Press, Chicago, IL, USA.

[22] Gustav Fechner and Helmut E. Adler. 1966. Elements of psychophysics. In *A Henry Holt Edition in Psychology*. H.H. Davis and E.G. Boring (Eds.), Holt, Rinehart and Winston, Michigan, USA.

[23] Kresimir Matekovic, Laszlo Neumann, Atilla Neumann, Thomas Psik, and Wener Purgathofer. 2005. Global contrast factor – a new approach to image contrast. In *Proceedings of the 1st Eurographics Conference on Computational Aesthetics in Graphics, Visualization and Imaging*, 159–167.

[24] Alessandro Rizzi, Thomas Algeri, Giuseppe Medeghini, and Daniele Marini. 2004. A proposal for contrast measure in digital images. *Image Processing* 1 (2004), 275–278. DOI: https://doi.org/10.1109/ICIP.2004.1421204

[25] Eli Peli. 1990. Contrast in complex images. *Journal of the Optical Society of America. A, Optics and Image Science* 7, 10 (1990), 2032–2040. DOI: https://doi.org/10.1364/JOSAA.7.002032

[26] Leonid L. Kontsevich and Christopher Tyler. 1999. Nonlinearities of near-threshold contrast transduction. *Vision Research* 39, 10 (1999), 1869–1880. DOI: https://doi.org/10.1016/s0042-6989(98)00274-3

[27] Andrew M. Haun and Eli Peli. 2013. Perceived contrast in complex images. *Journal of Vision* 13, 13 (2013), 3. DOI: https://doi.org/10.1167/13.13.3

[28] Siobhan Rockcastle and Marilyne Andersen. 2014. Measuring the dynamics of contrast & daylight variability in architecture: A proof-of-concept methodology. *Building and Environment* 81 (2014), 320–333. DOI: https://doi.org/10.1016/j.buildenv.2014.06.012

[29] Siobhan Rockcastle, Maria Amundadottir, and Marilyne Andersen. 2017. Contrast measures for predicting perceptual effects of daylight in architectural renderings. *Lighting Research & Technology* 49, 7 (2017), 882–903. DOI: https://doi.org/10.1177/1477153516644292

[30] Peter R. Boyce and Peter Raynham. 2010. Book review of the SLL lighting handbook. *Lighting Research & Technology* 42 (2010), 123–124. DOI: https://doi.org/10.1177/1477153510361278

[31] Liliana Albertazzi, Luisa Canal, Paolo Chisté, Rocco Micciolo, and Daniele Zavagno. 2018. Sensual light? Subjective dimensions of ambient illumination. *Perception* 47, 9 (2018), 909–926. DOI: https://doi.org/10.1177/0301006618787737

[32] Bahar G. Kumsar. 2020. Deciphering the Architectural Atmosphere through Atmospheric Moods: An Alternative Space Reading. Master's thesis. Istanbul Technical University, Istanbul, Turkey.

[33] Rainer Mausfeld. 2011. The perception of material qualities and the internal semantics of the perceptual system. In *Perception Beyond Inference: The Information Content of Visual Processes*. L. Albertazzi, G. Van Tonder, and D. Vishwanath (Eds.), MIT Press, Cambridge, MA.

[34] Xiaoyu Liu, Ming R. Luo, and H. Li. 2015. A study of atmosphere perceptions in a living room. *Lighting Research & Technology* 47, 5 (2015), 581–594. DOI: https://doi.org/10.1177/1477153514528934

[35] Yan Lu, Wi Li, Wei Xu, and Yandan Lin. 2019. Impacts of LED dynamic white lighting on atmosphere perception. *Lighting Research & Technology* 51, 8 (2019), 1143–1158. DOI: https://doi.org/10.1177/1477153518823833

[36] Seden Odabaşıoğlu and Nilgün Olguntürk. 2015. Effects of coloured lighting on the perception of interior spaces. *Perceptual and Motor Skills* 120, 1 (2015), 183–201. DOI: https://doi.org/10.2466/24.PMS.120v10x4

[37] *Python*. 2022. *Python, Ver. 3.10.4*. Python, Wilmington, DE. [Software].

[38] Michael Stokes, Matthew Anderson, Srinivasan Chandrasekar, and Ricardo Motta. 2003. A standard default colour space for the internet. In *Multimedia Systems and Equipment: Colour Measurement and Management*. J.P. Allebach (Ed.), SPIE, Bellingham, WA.
[39] *Shine Toolbox*. 2021. *Shine Toolbox, Ver. 0.0.3*. MIT. [Software].
[40] Richard L. Gorsuch. 1983. *Factor Analysis* (2nd ed.). Lawrence Erlbaum Associates, Hillsdale, NJ.
[41] Larry Hatcher. 1994. *A Step-by-Step Approach to Using the SAS System for Factor Analysis and Structural Equation Modelling*. SAS Institute, Cary, NC.
[42] *SPSS*. 2001. *SPSS, Ver. 28*. IBM, Armonk, NY. [Software].
[43] Henry F. Kaiser. 1960. The application of electronic computers to factor analysis. *Educational and Psychological Measurement* 20, 1 (1960), 141–151. DOI: https://doi.org/10.1177/001316446002000116
[44] Deborah L. Bandalos and Meggen R. Boehm-Kaufman. 2008. Four common misconceptions in exploratory factor analysis. In *Statistical and Methodological Myths and Urban Legends: Doctrine, Verity and Fable in the Organizational and Social Sciences*. C. E. Lance and R. J. Vandenberg (Eds.), Taylor & Francis, New York, NY.
[45] Jospeh F. Hair, Rolph E. Anderson, Ronald L. Tatham, and William C. Black. 1995. *Multivariate Data Analysis*. Macmillan, New York, NY.
[46] Marjorie A. Pett, Nancy R. Lackey, and John J. Sullivan. 2003. *Making Sense of Factor Analysis: The Use of Factor Analysis for Instrument Development in Health Care Research*. Sage Publications Inc. DOI: https://doi.org/10.4135/9781412984898
[47] R. J. Hawkes, Duarte B. Loe, and E. Rowlands. 1979. A note towards the understanding of lighting quality. *Journal of the Illuminating Engineering Society* 8, 2 (1979), 111–120.
[48] Tonino Griffero. 2014. Architectural affordances: The atmospheric authority of spaces. In *Architecture and Atmosphere*. P. Tidwell (Ed.), Tapio Wirkkala-Rut Bryk Foundation, Helsinki, Finland.
[49] Gernot Böhme. 2017. *Atmospheric Architectures: The Aesthetics of Felt Spaces*. Bloomsbury, London, UK.

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