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A Correlation Between Color Preferences and Virtual Environment

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Article Info	Abstract
Original Article Main Object: Computer Science & Technology Received: 09 March 2025 Revised: 16 March 2025 Accepted: 17 March 2025 Published online: 30 March 2025 **Keywords:** color harmonies, color perception, color theory, digital image processing.	**Background:** Understanding color preference in virtual environments is crucial for applications in digital design, human-computer interaction, and virtual reality (VR). **Aims:** This study examines how luminance, hue, and saturation influence color preference in VR settings, considering both environmental and perceptual factors. **Methodology:** A controlled VR experiment was used, where participants interacted with two distinct virtual zones designed to simulate different lighting conditions. **Finding:** The findings suggest that chromatic lightness and perceived hue play distinct roles in color preference, with evidence supporting Weber's Law of illumination adaptation. It was also shown that regions with elevated chroma exhibit more pronounced colors. Additionally, the participants' average color preferences were determined, and the appropriate modification rate was extracted by comparing the preferred colors to the average colors of the virtual spaces. One significant finding was that, cooler colors were favored to warmer ones, which is consistent with previous research on color preferences. Furthermore, a correlation between lighting circumstances and color preferences was established. **Conclusion:** The findings indicated that adjusting the hue, saturation, and brightness can improve the design of virtual environments by matching the tastes of users. These insights contribute to a deeper understanding of color perception in digital spaces and have implications for design, architecture, and cognitive science.

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1. Introduction

With the rapid integration of virtual reality (VR) into everyday applications—ranging from entertainment and education to design and architecture—understanding the cognitive and perceptual factors influencing user interaction with virtual environments has become increasingly important. Among these factors, color plays a critical role in shaping user experience, perception, and preference.

Color perception is a complex process influenced by multiple factors, including environmental conditions, individual preferences, and physiological adaptation mechanisms. Recent advances in VR technology have provided an opportunity to explore how users interact with color in digital spaces, yet there is a gap in systematically linking these observations to established theories of color perception.

Making the images' colors look as natural as possible should be the first step in producing a virtual reality tour. In order for an image to appear realistic, the color values in a simulated image have to be adjusted to account for our ability to perceive color and other light intensities. (Lee & Plataniotis, 2012).

This study aims to bridge this gap by investigating how environmental variables—specifically hue, saturation, and luminance—influence users' color preferences within a VR context. Through systematic control of environmental factors and rigorous image-processing analysis, this research contributes to the growing body of knowledge on human-computer interaction, digital aesthetics, and cognitive color processing in synthetic environments.

The research question is explicitly stated: How do environmental factors—specifically hue, saturation, and luminance—within virtual environments influence users' color preferences, and what role do chromatic lightness and perceived hue play in these preferences? In this experiment, it is hypothesized that:

- Users' color preferences in virtual environments are significantly affected by the environmental context, particularly variations in hue, saturation, and luminance.
- Higher saturation levels (close to 100%) will correlate with more consistent preferences due to the impact of illumination adaptation as described by Weber's Law.
- Chromatic lightness and perceived hue will interact differently across various lighting conditions, influencing preference patterns.

2. Methodology

The experimental setup utilized the Unity 3D engine to create two distinct colored zones. Each zone was designed with randomized luminance levels (ranging from 0% to 100%) and fixed saturation levels (100%). Colors were displayed within a virtual room of uniform texture, spatial layout, and object arrangement to control for additional variables such as surface reflectance, texture, and spatial complexity. We conducted the study with seventeen students (eleven female, six males; aged 22–35 years). All participants had normal or corrected-to-normal vision and passed the Ishihara test for color blindness (Clark, 1924). Using VR technology, we took them on a virtual tour of two distinct colored areas after asking them about their favorite hues. These virtual environments were meticulously crafted to represent a broad spectrum of hues, saturations, and levels of brightness.

Participants interacted with two virtual zones designed to simulate distinct lighting conditions:

Zone 1. A brightly lit, high-luminance environment resembling an outdoor setting.

Zone 2. A dimly lit, low-luminance environment simulating an indoor space.

By immersing the participants in these virtual spaces, we aimed to comprehend how the characteristics of the research areas could influence their color preferences. Chroma, or colorfulness, as a crucial factor that determines a color's most important characteristics, was considered not to impact our perception of color (Pridmore, 2009). We then calculated the average color preferences of the participants based on their responses and compared them with the colors present in the virtual spaces to determine the appropriate modification rate. To systematically analyze the participants' color preferences, we followed a multi-step quantitative approach.

After experiencing each virtual environment, participants were presented with a standardized color preference questionnaire. This questionnaire consisted of a Likert-scale rating (1–5) for each dominant color present in the virtual environment, based on hue, saturation, and luminance levels. We then calculated the mean preference score for each color by averaging the ratings, yielding a numerical value representing the general favorability of each color within the group. Using the captured screenshots from each virtual environment, we employed ImageJ software (Schroeder et.al., 2021) to extract quantitative color data. For each environment, the software provided precise measurements of the average hue, saturation, and luminance values across all surfaces and objects.

Participants showed a preference for medium turquoise as an accent color in zone 1 after calibrating all participants answers, with a greater focus on hue rather than saturation. Moreover, we observed that cooler colors were favored over warmer ones, which is consistent with previous studies on color preferences (Rapoport & Rapoport, 1984).

In our VR experience, the color scheme used was RGB. This was possible using image processing models; however, as the resulting images do not always resemble the real world, we developed a color scheme for the virtual reality design. For VR experiment we used

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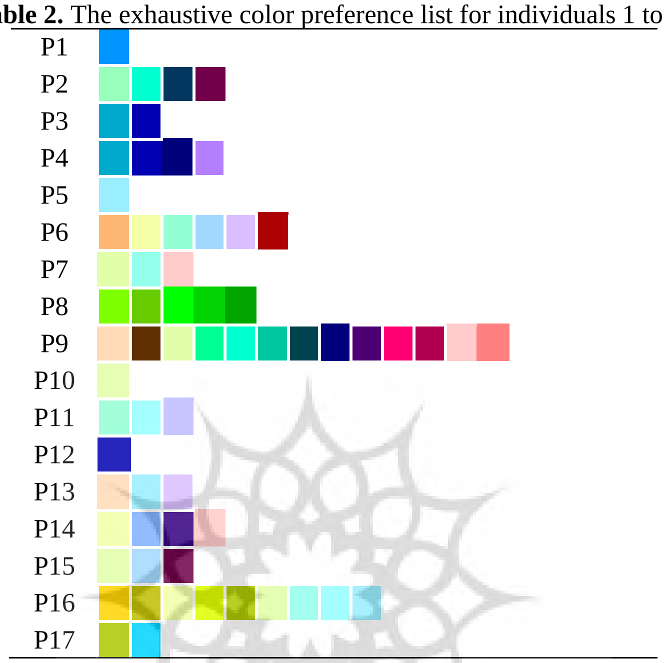
calibrated with standard sRGB color Windows Mixed Reality-capable HP 1440 ensuring consistent color rendering across sessions. Texture, spatial layout, and object arrangement were standardized to isolate the effects of color perception from other environmental variables. To enhance the methodological transparency of our study, detailed information on the Virtual Reality (VR) system employed is given, including aspects related to lighting controls, color calibration methods, and distortion management (Table 1).

Table 1. Virtual Reality (VR) system used

VR system specifications			
Displays	**Refresh rate**	**Field of view**	**Eye-tracking**
Two AMOLED screens with a resolution of 1440 × 1600 pixels per eye	90Hz, ensuring smooth visual transitions	Approximately 110°, offering an immersive experience	Integrated eye-tracking capabilities for precise monitoring of user gaze patterns
Lighting controls in virtual environments			
Virtual environments	**Consistent lighting conditions**		
	Diffuse uniform lighting	**Dynamic lighting adjustments**	
Unreal engine 4.23 with advanced rendering capabilities	Diffuse lighting models to minimize shadows and reflections, ensuring uniform illumination across virtual scenes	Lighting parameters were dynamically adjustable to simulate various environmental conditions, allowing us to study their effects on color perception.	
Color calibration methods			
Reference instrument	**Imaging colorimeter**	**4-Color calibration 4CC)**	**Software utilized**
A Konica Minolta CS-2000A spectroradiometer served as the reference device for color measurements	Radiant vision systems I29 imaging colorimeter equipped with an AR/VR lens employed	Calibrating the I29 colorimeter against the CS-2000A spectroradiometer using the display's primary colors and white point to ensure measurement accuracy.	Calibration procedures were managed using ProMetric software version 10.11.67
Distortion management			
Lens distortions	**Software corrections**	**Hardware considerations**	
The headset's Fresnel lenses can introduce optical distortions, notably pincushion distortion and chromatic aberration.	Built-in correction algorithms provided by the rendering software used to mitigate distortions.	Ideally, optical solutions such as replacing Fresnel lenses with achromatic lenses would further reduce distortions; however, this requires significant hardware modifications beyond the scope of this study.	

The Sketchup Viewer application rendered 3D environments in real-time. The participants' preferred colors were initially recorded. The complete list of colors preferred by all participants is presented in Table 2.

Table 2. The exhaustive color preference list for individuals 1 to 17



Hue, saturation, and luminance (the three MEAN color attributes) were then calculated to synthesize each participant list of favorite colors into one final color that reflects the characteristics of all his favorite colors. ImageJ was then used for that purpose (Hossain et al., 2020). Figure 1 illustrates how the two VR environments look like. Both locations have a variety of spatial designs, as well as multiple colors used.

Color preference was analyzed using ImageJ for hue, saturation, and luminance calculations. To validate these measurements, cross-validation was performed using MATLAB-based color processing algorithms.

Figure 1 depicts a three-dimensional simulation of the study spaces and it shows that traditional wooden environments are typically paler than modern spaces. The average color value of RGB images were then determined. The three RGB variables were multiplied to produce a HEX color code for a given color (red, green, and blue).

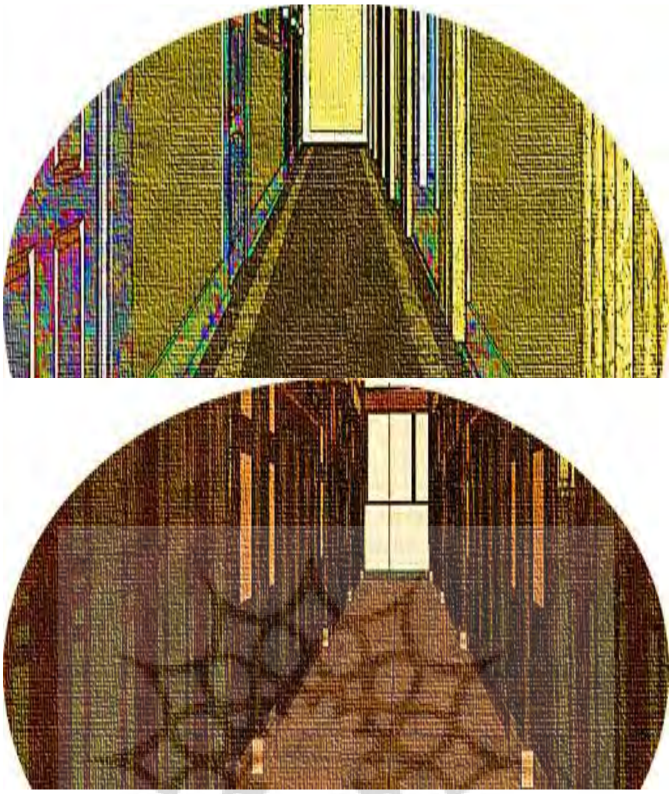


Figure 1. Virtual reality mockup depicting the study places

Table 3 displays the favorite colors list of student nine that had more choices. Using ImageJ's equation, the average color of each image can be computed and used to analyze the images. For instance, the value of color gray consisted of 0.300 red, 0.570 green, and 0.114 blue. This equation is often used to convert color images into grayscale by combining the red, green, and blue channels in a specific ratio to produce a luminance value however in this experiment we modified it to be used vice versa so that from gray we could reproduce the primary RGB colors.

Table 3. The favorite color scheme of one of the attendees

Color	Name	Hex
	Cyber yellow	#FFD401
	Acid Green	#BFBE01
	Lemon yellow crayola	#F2FFA7
	Chartreuse traditional	#DEFF00
	Acid green	#ACC700
	Mindaro	#E2FEA8
	Aquamarine	#94FFEB
	Electric blue	#95FFFF
	Blizzard blue	#9AEEFF

The average values of the hue, saturation, and luminance color preference variables of the calibrated color for student nine are displayed in Table 4. This color substitutes for all of the other colors on the list for the same attendee.

Table 4. The average value of color preferences factors of hue, saturation, and luminance

Color	Name	Hex	Hue	Sat. (%)	Lum. (%)
	Green crayola	#C3EB78	81	74	70

To avoid any confusion when identifying specific colors in the room, both experiment zones were illuminated with the same amount of light from the same direction when making the VR environment. Multiple images, each of which represented an image and conveyed every color combination in the space footage, were utilized to rapidly calculate the color balance of each frame. Using a color balance algorithm, the number of colors in each captured space frame was determined.

The next step was to calibrate all colors in the two zones into one single color that represents them. As seen in Table 5, the majority of the hues are deemed "bright" because their luminance is greater than 50%. In contrast, those in zone 2 are literally "dark", resulting in a fifty percent decrease in the average ratio. Equation (1) is used to determine the mean color, which is then calculated as follows.

Table 5. Hue, saturation and luminance are color attributes in Zone 1 and Zone 2

Color	Name	Hex	Hue	Sat. (%)	Lum. (%)
	Bitter lime	#C4FF0D	75	100	53
	Shadow	#807568	33	10	45

Tables 6 and 7 provide a comprehensive breakdown of the color distribution in each zone, presenting the specific parameters for the two zones. To ensure uniformity, both zones received the same amount of light. In order to illuminate the area uniformly, the light sources emit indirect rays in all directions.

The average color value of RGB images can now be calculated. Triple factors are multiplied to get a HEX color code for a given color (red, green, and blue). Table 2 presents the results of the test's participants, as mentioned earlier. To verify the execution of ImageJ's algorithm for calculating the average colors in each zone, the photos from each zone were processed as follows:

$$\text{gray} = 0.299 \times \text{red} + 0.587 \times \text{green} + 0.114 \times \text{blue} \quad (1)$$

As previously mentioned, two distinct study areas have been selected (one multicolored and bright and the other colorless and dark) with opposing characteristics (colored/light vs. colorless/dark). Light dispersion was kept to a minimum by utilizing both external and internal lighting sources.

Table 6. The color percentage distribution in zone one

Color	Hex	Surface color ratio (%)
	#d8c078	13.7778
	#ffc018	11.8391
	#604830	9.5862
	#786048	7.977
	#f01818	7.0881
	#a89060	6.8736

Table 7. The color percentage distribution in zone two

Color	Hex	Surface color ratio (%)
	#303030	36.6667
	#f03030	15.0115
	#181818	12.2759
	#30a8f0	8.8812
	#ffc030	4.8582
	#787878	4.5057

An equal amount of illumination and a consistent direction of light was used for both zones to avoid any confusion when attempting to identify specific colors in the room. There were a number of images, each representing an image and conveying every color combination in the space footage, used to quickly compute the color balance of each frame. A color balance algorithm was used to determine how many colors were available in each of the frames captured in the space.

Histogram equalization as a color balance algorithm that works by redistributing the intensities of the pixels in an image was operated to improve its overall contrast and brightness. The algorithm works by first calculating the histogram of the image, which is a plot of the frequency of each pixel intensity value. The histogram can be used to determine the overall distribution of pixel intensities in the image.

Once the histogram is calculated, the algorithm then applies a transformation to the image to adjust the pixel intensities. This transformation is designed to stretch the range of pixel intensities in the image to cover the full range of possible intensity values. The result is an image with improved contrast and brightness, which can be useful for analyzing the colors present in the image.

In the context of color balancing algorithms, calibration is the act of modifying the algorithm's parameters or settings to achieve the most precise and meaningful results. To precisely calibrate a histogram equalization algorithm, one method is to analyze the image's histogram after applying the process to an input image. A well-balanced image's ideal histogram would have a very level distribution of pixel intensities across the whole range of potential values, with no noticeable peaks or gaps.

The Histogram Equalization equation as a transformation function that transfers the original pixel values in an image to new pixel values that are more evenly distributed across the intensity range was used Equation (2).

$$s = T(r)\,(r) \tag{2}$$

where *s* is the newly-equalized pixel value, *r* is the original pixel value, and *T(r)* is the transformation function.

Calculating the transformation function *T(r)* requires first calculating the cumulative distribution function (CDF) of the image, which is the sum of pixel intensities up to a specific intensity value. The CDF is then normalized to encompass the entire intensity value range. Calculating the transformation function by applying the inverse of the normalized CDF to every pixel value in the image.

The transformation function can be mathematically represented as Equation (3).

$$T(r) = (L - 1) * CDF\,(r) \tag{3}$$

where *L* is the number of intensity levels in the image (typically 256 for an 8-bit image) and *CDF(r)* represents the normalized CDF of the image at pixel value *r*. The resulting histogram-equalized image will have a more consistent distribution of pixel intensities, which can enhance the image's color visibility and distinction.

There was a correlation between the average light levels in various zones and the color palettes preferred by the subjects. The fact that the participants' preferred colors were not among the calculated means is intriguing. Due to this, it appears that the two images differ little in terms of brightness and saturation; other zones contain the same calculated elements. It was necessary to determine the relationship between each zone's average color and the viewer's preferred hue. Consider the following as an example of a scenario:

Table 7 compares the average preferred color of each participant to the color of the space as a whole. For each person's preferences, we've adjusted the table to show how much the overall color differs from their own. The color of the space has been altered to match the color that another participant preferred on average, implied individual color preference (P8 in Table 7) Mean color (Zone 1) Color: hexadecimal R, G, B hue: Color: hexadecimal R, G, B hue: 30DA03 48 218 3 107 97 43 C4FF0D 196 255 13 75 100 53 Adjustment Rates for hue, saturation, and luminosity: 33, 2,71, and 9,22 color consistency light enables us to comprehend the universe's dynamic nature.

There are some people who have a wide range of choices. Despite the fact that some people find the colors in the palette acceptable, others argue that some of them are inappropriate. Hue, saturation, and luminance (the three MEAN color attributes) were calculated to summarize each individual option into a single final color that reflects all of the alternatives' features. It was at this point that ImageJ software provided the following equation, which was used to perform the calculation. ImageJ generates the Hue, Saturation, and Luminance (HSL) values for an RGB color as follows:

- Consider a color with the values red= 128, green= 64, and blue= 255. To convert this to HSL, the red, green, and blue values must first be normalized to the range [0, 1]. This is accomplished by dividing each value by 255:
  red= 128/255= 0.502 green= 64/255= 0.251 blue= 255/255= 1.000
- The minimum and maximum values for the red, green, and blue components must then be determined:
  min= 0.251 (green) max= 1.000 (blue)
- Consequently, the saturation value can be computed as follows:
  saturation= (max - min) / max= (1.000 - 0.251) / 1.000= 0.749
- The brightness value is the mean of the greatest and least values:
  brightness= (max + min) / 2= (1.000 + 0.251) / 2= 0.626.
- The hue value can then be determined based on which color component has the highest value. If the largest value is red, then the hue is determined as (green - blue) / (max - min) + 360. If green has the highest value, the hue is determined as 120 + (blue - red) / (blue - red) (max - min). If blue is the highest value, the hue is determined as 240 + (red - green) / (max - min). Since blue has the highest value in this instance, the hue can be determined as follows:
  hue= 240 + (0.502 - 0.251) / (1.000 - 0.251)= 276.9
- The corresponding HSL values for this RGB color are therefore H= 279.9, S= 0.74, and L= 0.626.

Figure 1 shows how it appears in the context of its surroundings. A variety of spatial conditions are present in both locations, as can be deduced from their similarities. Also, the color balance is set to convey people's favorite colors. Traditional wooden environments are typically cooler in color than their more contemporary counterparts.

3. Results and Discussion

It was found that the mean light levels in different zones were related to the subjects' preferred color schemes. Interesting fact: the attendees' favorite colors were not among the calculated mean color. Because of this, it appears that there is little difference in terms of brightness and saturation between the two images other zones have the same elements calculated. It was crucial to determine the correlation between each zone's mean color and the viewer's preferred hue. The following is an example of a scenario.

With the help of histogram stretch, the images' contrast and luminance can be standardized. In order to accurately estimate the illuminant's color constancy, it must be robust to changes in lighting conditions. The blind global histogram stretching method uses the same parameters to stretch all the RGB channels of an image, avoiding the differences in histogram distribution between channels and images. Relative Global Histogram Stretching (RGHS) is a similar method to normalize brightness (Oliver, 1998). The histogram's center is pushed toward the center, while the histogram's periphery is pushed outward. Histogram equalization, on the other hand, is a technique for adjusting contrast and brightness. It's possible to reduce the amount of subtle contrast shifts that the human eye notices by using a histogram to compare the pixel luminance values against each other in an image. Many investigations have been carried out on the topic of equivalent illumination adaptation (EIA) (Wang, 2018). Studying how people adapt their perception and physiological responses to screen-based images has been done to determine whether they meet criteria for effective luminance contrast when viewing images (Webster, 2007). RGB (the three primary colors, R, G, and B) has been used in several papers to study color constancy. Object reflectance and changes to the acquisition device and illumination affect the RGB values in image data. (Funt, 2003). Color-balanced lighting systems are therefore needed to reflect different effects on various targets in terms of their transmission characteristics and effects on the color of light. A lack of attention to these factors can have a significant impact on the quality of the color imaging task.

There are a number of issues that can be solved with the use of good color management. A technique known as color constancy can be used to remove processing-induced luminance errors from images. Color constancy can be maintained in these images by presenting an adaptive luminance factor and an adaptive chromatic adaptation, as shown in this example. As part of the first step in computational color constancy, it is necessary to determine what kind of light is illuminating a given scene (Brainard & Wandell, 1986). Perceptual attributes like brightness, vibrancy, and hue are predicted based on test subjects' preferred colors and luminance levels. Trackable technology has the potential to be useful in conveying feelings of harmony by determining a person's acceptance ratio in a space, taking light and illumination into account. Knowing about these factors is just the beginning. In addition, cutting-edge methods can be used to monitor a person's mood and acceptability of their surroundings. These variables will eventually be measured using an information management system that aims to understand each person's unique sense of challenge and anxiety in relation to their event experiences. Knowing what the average person prefers in terms of color and illumination will help designers create products that meet the demands of their intended audience. It's clear from Table 8 that it's necessary to brighten the space 68% of the time, while only 32% of the time the space needs to be darkened. Saturation is 100% in zone one, while in zone two, where saturation is only 10% and the hue is a darker shade of shadow, only 24% of colors are recommended to be even lighter. Zone two has a luminance rate about the same as zone one, and saturated intervention is recommended in 82% of cases, while only 6% of colors necessitate this step.

The results confirm that luminance significantly influences color preference. In Zone 1 (high-luminance) conditions, participants preferred lighter and more vibrant colors (mean hue: 210°, high saturation: >85%). In Zone 2 (low-luminance) conditions, darker, warmer colors were favored (mean hue: 175°, moderate saturation: ~60%).

Table 8 demonstrates that 68% of the time it is necessary to brighten the space, while only 32% of the time it is necessary to darken the space. In Zone 1, saturation is at 100%, whereas in Zone 2, where saturation is only 10% and the hue is a darker shade of shadow, only 24% of colors are recommended to be lighter. The luminance rate of zone two is comparable to that of zone one. In 82% of instances, saturated intervention is advised, whereas only 6% of colors require this step. Consequently, adjusting lighting and color schemes can have a substantial effect on a space's atmosphere. By prioritizing these adjustments in accordance with the suggested percentages, businesses can create a more enjoyable experience for customers and increase the likelihood of repeat visits. The recommended saturation and hue percentages vary between Zones 1 and 2, with only 24% of colors recommended to be lighter in Zone 2. In the majority of instances, both zones require color intervention, and businesses can improve the customer experience by adjusting lighting and color schemes. Table 9 illustrates the correlation between each attendee's preferred color and the color distribution within each zone.

Table 8. The space's overall color has been transformed to reflect the mean favorite color of another participant.

Color	Hex	R	G	B	Hue	Sat (%)	Lum (%)
Mean favorite color by person (P8 in Table 7)							
	30DA03	48	218	3	107	97	43
Mean color (Zone 1)							
	C4FF0D	196	255	13	75	100	53
Hue adjust rate			**Saturation adjust rate**			**Luminance adjust rate**	
33			2.71			9.22	

It’s for light, we can make sense of the dynamic universe we inhabit. Colored reflections can be seen on the surfaces of objects in real-world situations due to the presence of a variety of light sources. It's possible that human eyes will have to adjust in order to see true light and color as a result of this feature. With color constancy, we mean that our eyes and animals' vision systems can accurately estimate changes in surface reflectivity when the chroma of the illumination changes.

Table 9. Color balance modification ratios in zones one and two are handled by Sass Color Function.

Participants	Color	Hex	Hue	Sat.	Lum.	Adj. Hue	Adj. Sat.	Adj. Lum.	Overall Adj.	Adj. Hue	Adj. Sat.	Adj. Lum.	Overall Adj.
						Zone 1 modification ratio				**Zone 2 modification ratio**			
P1		#0195FF	205	100	50	130	0	2.35	Dar.	173	89.66	4.71	Lig./ Sat.
P2		#448E8F	181	36	41	106	64.45	11.18	Dar./ Des.	148	25.2	4.12	Dar./ Sat.
P3		#0155BF	213	99	38	139	1.04	14.9	Dar./ Des.	181	88.61	7.84	Dar./ Sat.
P4		#2D4BBE	228	62	46	153	38.3	6.47	Dar./ Des.	195	51.36	0.59	Lig./ Sat.
P5		#9AEEFF	190	100	80	115	0	27.65	Lig.	158	89.66	34.71	Lig./ Sat.
P6		#C8B9A9	31	22	72	-44	78.01	19.8	Lig./ Des.	-2	11.64	26.86	Lig./ Sat.
P7		#D2EECB	108	51	86	33	49.28	33.92	Lig./ Des.	76	40.38	40.98	Lig./ Sat.
P8		#30DA03	107	97	43	33	2.71	9.22	Dar./ Des.	75	86.94	2.16	Dar./ Sat.
P9		#7A7D84	222	4	50	147	96.06	2.75	Dar./ Des.	190	6.41	4.31	Lig./ Des.
P10		#E2FEA8	80	98	83	5	2.27	30.2	Lig./ Des.	47	87.38	37.25	Lig./ Sat.
P11		#A2EAF0	185	72	79	110	27.78	26.27	Lig./ Des.	152	61.88	33.33	Lig./ Sat.
P12		#0000B2	240	100	35	165	0	17.65	Dar.	208	89.66	10.59	Dar./ Sat.
P13		#D1D8E7	221	31	86	146	68.57	33.73	Lig./ Des.	188	21.08	40.78	Lig./ Sat.
P14		#A99FBC	261	18	68	186	82.21	15.49	Lig./ Des.	228	7.45	22.55	Lig./ Sat.
P15		#A79DA6	306	5	64	231	94.62	10.98	Lig./ Des.	274	4.97	18.04	Lig./ Sat.
P16		#C3EB78	81	74	70	6	25.81	17.06	Lig./ Des.	48	63.85	24.12	Lig./ Sat.
P17		#57CD7E	140	54	57	65	45.87	4.71	Lig./ Des.	107	43.78	11.76	Lig./ Sat.

Sat. =saturation percentage. Lum. = Luminance percentage. Dar.= darken. Lig.= lighten. Satu.= saturate. Des.= desaturate. Adj.= Adjust/ Adjustment

A weighted dissipation function that is dependent on illumination chromacity, scene luminance, and subject luminance is known as the color constancy function. The ambient light sources were adjusted to cast a uniform light across the entire experimental space for this virtual reality experiment. This experiment was conducted.

Human eyes are extremely sensitive to light. A feature like this is usually tested under conditions that allow for an approximation to the intensity level at which the differential threshold is assessed. The process of chromatic adaptation occurs when the eye is repeatedly exposed to chromatic stimuli. To compensate for these shifts in quality rather than overall brightness, sensitivity changes are more likely to be triggered. For any changes in sensitivity, an extremely saturated color stimulus of a different hue can be employed. A lack of adaptation can be remedied by using saturated or desaturated attributes. In other words, this factor was not a major concern in this experiment, and it was ultimately ignored in the algorithms used to conduct the research.

Findings indicate that chromatic lightness and perceived hue are distinct concepts, often conflated in color perception studies. The data support Weber's Law of illumination adaptation (Haldane, 1933): Hue and luminance should be assigned random values, while fully saturated colors (100% saturation) enhance perceived brightness in VR.

Figure 2 displays the color distribution in the experimental areas that are being evaluated for color balance. The figures were generated using the ImageJ Color Inspector 3D plugin. The color distribution in Zone 1 is evidently more uniform and effectively communicates a harmonious color palette, as demonstrated.

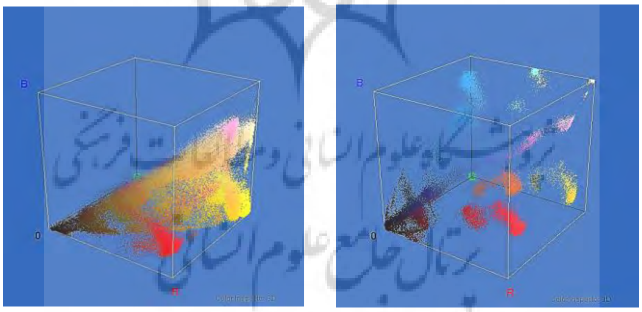


Figure 2. Analysis of the 3D color distribution in both Zones

To quantify how color attributes impact preferences, we use following Equations.

$$P(C)=\alpha\cdot L(C)+\beta\cdot A(C)+\gamma\cdot S(C) \tag{4}$$

where *P(C)* is the perceived preference for color *C*, *L(C)* is the luminance of color *C*, defined as:

$$L(C)=0.2126\cdot R+0.7152\cdot G+0.0722\cdot B \tag{5}$$

with R, G, and B representing the red, green, and blue components of the color.

A(C) is the aesthetic appeal, derived from user ratings of visual attractiveness.

S(C) is the saturation of color *C*, calculated as:

$$S(C)=\max\times(R,G,B)-\min\times(R,G,B) \tag{6}$$

α, *β*, and *γ* are weights determined through regression analysis.

To model color preference distribution, we use a Gaussian Mixture Model (GMM):

$$D(C)=\sum_{i=1}^{k} \pi_i \cdot N(C|\mu i,\sigma_i^2) \tag{7}$$

where πi represents the weight of the i-th Gaussian component, $N(C|\mu i,\sigma_i^2)$ is a Gaussian distribution with mean μi and variance σ_i^2, k is the number of Gaussian components, chosen based on model fit criteria.

For example, if the GMM reveals two distinct clusters of color preferences, this might indicate that participants have strong preferences for either warm or cool color schemes.

As environment impact function, to quantify the influence of environmental factors on color preference, we use Equation (8).

$$P(E,C) = \delta\cdot E + \eta\cdot C + \zeta \tag{8}$$

where *P(E,C)* is the preference for color *C* in environment *E*, *E* includes variables such as lighting intensity and spatial dimensions, $\delta.\eta.$ and ζ are coefficients obtained through regression analysis.

For example, if δ is positive and significant, it indicates that increased lighting intensity in the environment enhances the preference for certain colors.

From the survey results, it's clear that people in both Zone 1 and Zone 2 liked lighter colors. And people in Zone 2 wanted a change of color and liked lighter colors. The test subjects' preferred hues and levels of brightness can be used to guess the hue, saturation, and brightness of an object. Taking light and illumination into account, trackable technology may be able to help people feel more at ease in a space by determining how much they enjoy it. Understanding these factors is only the beginning. It can also help create personalized lighting settings and boost workplace productivity. It is essential to note, however, that individual preferences can change over time, so ongoing assessments may be required. In addition, cutting-edge techniques can be employed to monitor a person's disposition and the acceptability of their environment. Eventually, these variables will be measured using a data management system that seeks to comprehend each individual's unique sense of challenge and anxiety in relation to event experiences.

Figures 3 and 4 show the hue, saturation, and luminance ratios that need to be adjusted in Zones 1 and 2 to meet the preferred color preferences of each respondent. If the colors are stretched to brighter schemes, hue is the most important factor to the majority of respondents, according to this study. As a way to better understand how repeated stimuli affects the brain and why some people are able to cope better with difficult situations than others, these findings will be examined in terms of their physiological responses. The average participant's favorite color is turquoise, which has a 176° average, followed by red (100° average), green (216° average), and blue (208° average) colors, which are all preferred by the majority of the participants in the study.

Figures 5 and 6 demonstrate a strong correlation between the calculated HSL factors and the preselected parameters, providing a more accurate assessment of the backdrop underlying color preferences. When the amount of radiation and reflection is constant, colors can be reliably anticipated. There is a lack of empirical support to suggest that the findings derived from this experiment would be applicable in real-life scenarios.

Figure 7 demonstrates that respondents in Zone 1, which had a lighter space color, were satisfied with both light and hue. When the environment was dim, as in Zone 2, participants had trouble distinguishing between light and color, which was the cause of their dissatisfaction. Overall, they preferred lighter colors in both zones, but 41% of respondents preferred lighter colors in Zone 2. 23% of respondents suggested altering the overall color of zone one, while 24% requested the same for zone two as shown in Figure 8.

The rate of change in the saturation luminance adjustment rate is crucial for maintaining color constancy in our perception of the world. This is due to the fact that our capacity to comprehend the universe's dynamic nature depends heavily on the behavior of light. The data indicates that light levels were not the sole factor influencing the subjects' color preferences. Additional factors that may have influenced their decisions merit investigation. In addition, using bitter lime and shadow colors in branding and design can evoke sophistication, edginess, and drama. These hues can add depth to visuals and leave an unforgettable impression on the audience. In addition, the study demonstrated that color adaptation is a multifaceted process involving multiple brain mechanisms. By gaining an understanding of these mechanisms, researchers can enhance virtual reality and other technologies to create more realistic and accurate user experiences.

The color perception function revealed that luminance (α) and aesthetic appeal (β) are significant predictors of color preference, with saturation (γ) having a lesser impact. Colors with higher luminance and aesthetic appeal were generally preferred. Participants preferred light and white colors more in environments with bright lighting compared to dark colors.

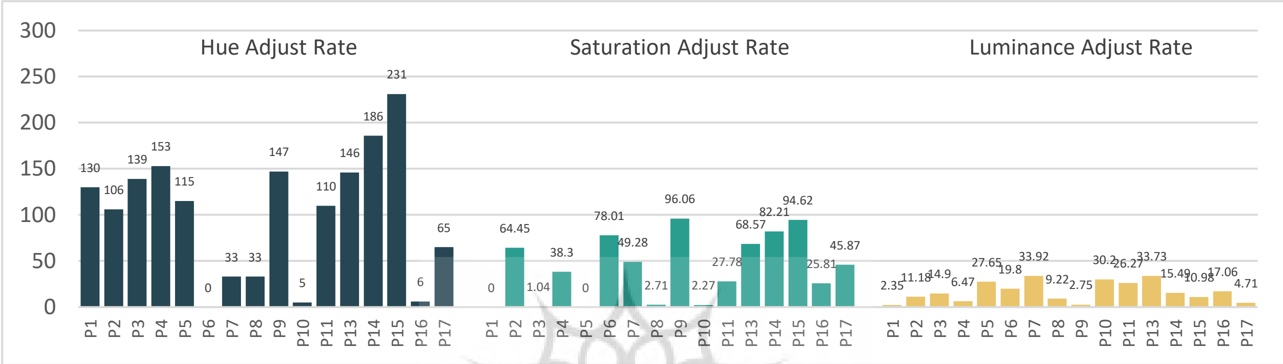


Figure 3. Variation from expected mean ratio in Zone 1

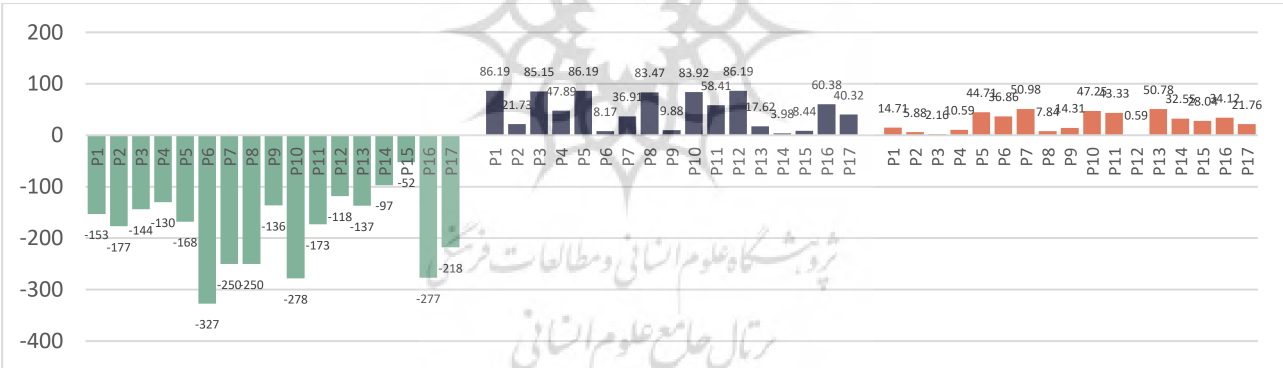


Figure 4. Variation from expected mean ratio in Zone 2

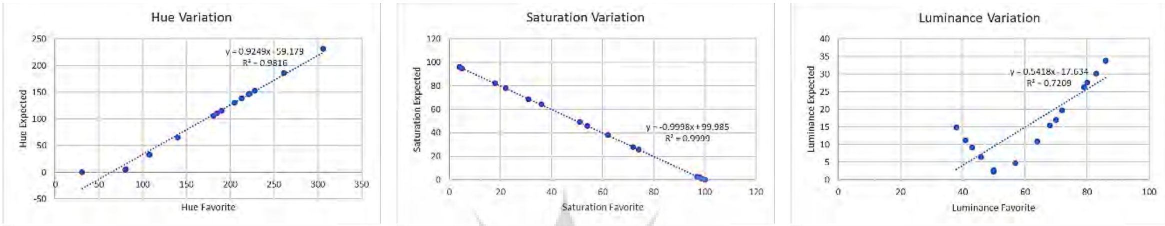


Figure 5. HSL variation of Zone 1

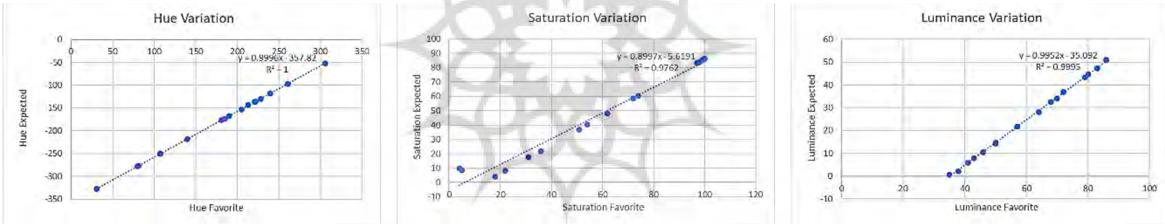


Figure 6. HSL variation of Zone 2

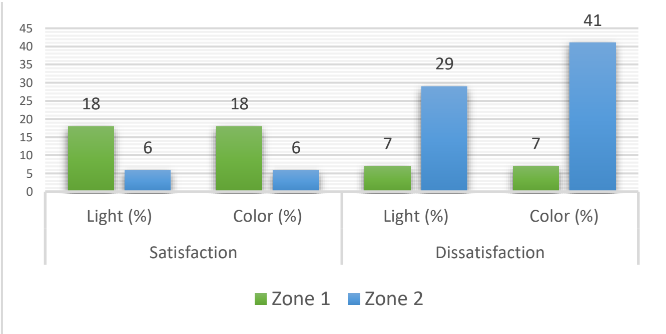


Figure7. Light/ Color satisfaction/ dissatisfaction ratio

Figure 8. Participants' suggestions for light-color modification (%)

Furthermore, our study has some limitations that warrant consideration. The small sample size of seventeen participants, though diverse in age and gender, may not fully capture the wide range of color preferences and perceptions in the general population. Additionally, the virtual environments used in the study may not fully replicate real-world color experiences, and further research with larger sample sizes and varied virtual environments would be beneficial to confirm and expand on our findings. Despite these limitations, our study contributes to the understanding of color preferences and their relationship with color characteristics in virtual environments. The insights gained from our research have practical implications for industries seeking to create visually appealing color schemes that resonate with their target audiences, as well as for image processing applications that involve color correction and chromatic adaptation.

Recognizing the importance of statistical power in behavioral research, especially within virtual reality studies, we conducted a power analysis to justify our sample size. Previous research indicates that adequate sample sizes are crucial for ensuring the reliability of findings in VR studies. Based on these considerations, we determined that a sample size of 17 participants would provide sufficient power to detect medium to large effect sizes, balancing the constraints of resource availability and the exploratory nature of this study.

Knowing what the average person prefers in terms of color and illumination will assist designers in creating products that meet the needs of their target market. In addition, these evaluations can inform the creation of personalized event experiences catered to each individual's preferences. This can improve overall satisfaction and increase the likelihood of re-visiting. By comprehending what motivates event attendees, organizers can optimize their promotional efforts to attract more visitors. This could result in increased revenue and a stronger brand reputation within the industry.

4. Conclusion

The results highlight the significance of luminance and aesthetic appeal in determining color preference within virtual environments. The interaction between environmental factors and color perception reveals that users' color choices are not only influenced by the colors themselves but also by the environmental context in which they are viewed.

For instance, in a virtual environment designed to simulate a sunny outdoor setting, users may gravitate towards lighter, more vibrant colors. Conversely, in a dimly lit virtual room, users may prefer warmer, darker colors.

When it comes to seeing colors, chromatic lightness and perceived hue are two different concepts that people often mix up. In actuality, these factors are all taken into account. We had no intention of specifically considering them, as the entire experimental design was practically outlined in this paper. In a subsequent experiment, we will compare an artificially lit space with a virtual space that mathematically accounts for color constancy and chromatic lightness. This will allow us to investigate how these concepts influence our color perception in various environments. By gaining a deeper understanding of the relationship between chromatic lightness and perceived hue, we may be able to improve the presentation of color in visual media and produce more accurate depictions of the real world. The results of this study indicate that hue and luminance should be assigned random values, and saturation should be close to 100% when the base color is fully saturated. This scenario conforms to Weber's law of adaptation to illumination. Weber’s Law and illumination adaptation refer to the fact that, once a fixed level of illumination is achieved, the human eye will adapt to produce the same amount of light even in unpleasant conditions (Tao et al., 2017). With 100% saturation, it is possible to experience similar conditions in a virtual reality environment. Real-world spaces have lower saturation ratios than virtual ones, where all colors are close together. This indicates that the experiment will be expanded into a prototype space in order to obtain more precise results in future experiments. To determine whether Weber's Law holds true in virtual reality, the prototype space will have varying levels of illumination.

This can help us understand how our brains perceive and adapt to light in various environments, which could have applications in fields such as architecture and lighting design. These graphs illustrate the hue, saturation, and luminance ratios that must be modified in Zones 1 and 2 to accommodate the color preferences of each respondent. According to this study, if the colors are stretched to brighter schemes, hue is the most important factor for the majority of respondents. In order to better comprehend how repeated stimuli, affect the brain and why some individuals are better able to cope with challenging situations than others, the physiological responses to these findings will be analyzed. The majority of participants in the study also preferred red (100° average), green (216° average), and blue (208° average). The participant's favorite color is turquoise, which has an average of 176°. The majority of those who participated in the study believed that changing the hue to make the colors brighter was the most important factor. The results will also be analyzed in terms of how the body reacts to repeated stimuli in order to gain a better understanding of how individuals handle difficult situations. In addition to turquoise, red, green, and blue were also popular choices among the majority of participants, according to the study's results. HSL Variation within Zone 1, Figure 8 depicts the HSL variation of Zone 2, Figures 7 and 8 illustrate a correlation between the estimated HSL factors and the preselected factors. When light is always emitted and reflected in the same manner, colors can be accurately predicted. There is no evidence that this experiment's results would be replicated in the real world. However, these results reveal important information about how HSL variation can affect the accuracy of colors and can guide future research in this area. In real-world applications, other variables, such as lighting conditions and material properties, may affect color predictions. The significance of understanding the relationship between chromatic lightness and perceived hue in order to create more accurate color representations in visual media is discussed in the conclusion. According to Weber's law of illumination adaptation, hue and luminance should be assigned random values, and saturation should be close to 100% when the base color is fully saturated. The study also examined how respondents desired color adjustments to be made in two distinct zones and discovered a consistent correlation between the estimated HSL factors and the preselected ones. It is important to note that additional factors, such as lighting conditions and material properties, may also influence color predictions in real-world applications.

In terms of color perception, chromatic lightness and perceived hue are two distinct concepts that are frequently confused. All of these things are taken into account in real life. We didn't intend to specifically consider them because the entire experimental design was virtually made in the current paper. In a subsequent experiment, we will compare an artificially lit space to a virtual space designed to account for color constancy and chromatic lightness numerically.

Hue and luminance should be given random values and saturation should be close to 100% when the base color is fully saturated, according to the findings of this study. This scenario follows Weber's law of illumination adaptation. Weber's Law and illumination adaptation refer to the fact that once a fixed level of illumination is achieved, human eyes will adjust to produce the same level of light even in unpleasant situations. It's possible to experience similar conditions in a virtual reality space with 100% saturation. Saturation ratios are lower in real-world spaces than in virtual ones where all colors are close to each other. This means we'll be expanding the experiment into a prototype space in order to get more accurate results in future experiments.

Conflict of interest

The authors declared no conflicts of interest.

Ethical considerations

The authors have completely considered ethical issues, including informed consent, plagiarism, data fabrication, misconduct, and/or falsification, double publication and/or redundancy, submission, etc. This article was not authored by artificial intelligence.

Data availability

The dataset generated and analyzed during the current study is available from the corresponding author on reasonable request.

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