Erciyes University Journal of Institue Of Science and Technology

Research Article
10.65520/erciyesfen.1821015

Imprint:
Volume: 42(1)
Year: 2026
Page: 1-12

Effects of Visual Color Stimuli on Brain Activity: An EEG-Based Study

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Received: 10/11/2025
Accepted: 2/24/2026

Citation:
Çiğdem Gülüzar Altıntop, Emre Erdoğan, Tolga Demren, Ahmet Calp & Furkan Kavaklı, (2026). Effects of Visual Color Stimuli on Brain Activity: An EEG-Based Study. *Erciyes University Journal of Institue Of Science and Technology*, 42(1), 1-12. https://doi.org/10.65520/erciyesfen.*1821015*

Abstract

Color perception is a multifaceted phenomenon due to the combined functioning of eye and brain. It has been shown that colors affect emotion and behavior. This study investigated the effects of different color stimuli on the brain using electroencephalography (EEG) signals. Twelve healthy individuals participated in the study and EEG was obtained using an 18-channel system while they were exposed to eight basic color stimuli. Features were extracted from the signals, and then several statistical analyses and topographic mapping were performed. Participants were divided into two groups and significant differences were observed between the groups, specifically in the temporal, parietal, and frontal regions. The cooler (blue, cyan) and neutral colors (black, white) demonstrated the most significant changes, while the warm colors (red, yellow, violet) produced widespread frontal-parietal activation. In the current analysis, complexity emerged as the indicator that produced the most significant differences. These findings suggest that color stimuli modulate cortical activation in a distinct way, and are subject to individual differences. Future studies will be conducted to further support these findings with larger samples, different intensities of color, and multimodal methods.

Keywords: EEG, Biomedical signal processing, Complexity, Brain-dynamics, Color perception

Görsel Renk Uyaranlarının Beyin Aktivitesine Etkisi: EEG Tabanlı Çalışma

Öz

Renk algısı, göz ve beynin etkileşimli işleyişiyle oluşan karmaşık bir süreçtir. Gerçekleştirilen çalışmalar renklerin hem duyguları hem davranışları etkilediğini göstermektedir. Bu çalışmada, farklı renk uyaranlarının beyindeki etkileri Elektroensefalografi (EEG) sinyalleri ile incelenmiştir. On iki sağlıklı katılımcı çalışmaya dahil olmuş ve katılımcılara sekiz temel renk uyaran olarak izletilirken 18 kanallı EEG kayıtları elde edilmiştir. Bu sinyallerinden çeşitli özellikler çıkarılmış ve istatistiksel analizler ile topografik haritalama yapılmıştır. Katılımcılar iki gruba ayrılmış ve gruplar arasında özellikle temporal, parietal ve frontal bölgelerde anlamlı farklılıklar gözlemlenmiştir. Soğuk (mavi, camgöbeği) ve nötr renkler (siyah, beyaz) daha belirgin değişiklikler oluştururken, sıcak tonlar (kırmızı, sarı, eflatun) geniş frontal-parietal aktivasyona neden olmuştur. Karmaşıklık özelliği anlamlı farklılığın en çok sağlandığı belirteç olarak öne çıkmıştır. Bulgular, renk uyaranlarının kortikal aktivasyon üzerinde belirgin ve bireysel farklılıklara bağlı etkiler yarattığını göstermektedir. Gelecek çalışmalarda daha geniş örneklem, farklı renk yoğunlukları ve multimodal yöntemlerle bu bulguların desteklenmesi planlanmaktadır.

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Anahtar kelimeler: EEG, Biyomedikal sinyal işleme, Karmaşıklık, Beyin dinamikleri, Görsel algı

1. Introduction

Visual perception in individuals is the result of the interaction of the eyes and the brain working together. While light enters the eyes and sends signals via the optic nerve, the brain interprets what was seen by creating vision in the visual cortex in the brain. This process is complex in nature because visual perception has visual stimuli, but it adds to its meaning and has knowledge about shapes and features such as color or depth [1]. Individual differences in the processing of information that takes place in the brain, in addition to the health of the eyes and previous visual experiences, can contribute to the processing of visual information, particularly for color [2]. To understand this process is greatly important for neuroscience and cognitive science literature when researchers study how the brain functions and responds to visual stimuli, specifically colors. Within the literature, there are many studies that show visual perception is processed in the brain, plus the effects of colors.

Recent studies have increasingly used EEG to investigate how the brain responds to color and other visual stimuli. For example, researchers have shown that rapid presentation of different color categories can elicit distinct EEG responses, suggesting that the visual cortex encodes color information even without explicit categorization tasks [3] . Another study has explored neural responses to RGB color stimuli, revealing differences in oscillatory patterns across frequency bands in occipital and frontal regions during color perception [4]. Additionally, investigations comparing EEG responses to cool, warm, and neutral hues in different participant groups have demonstrated variability in ERP components such as P2 and P3, highlighting how individual factors can influence color processing [5] . These studies underscore the utility of EEG in capturing both temporal and spatial aspects of brain activity in response to visual color stimuli and support the importance of feature-level analysis for understanding color perception mechanisms.

Roy et al. [6] examined the effects of color on EEG complexity and regional connectivity in the human brain. EEG data were collected from 16 channels while subjects viewed images of seven different colors on a gray background. Multi-fractal analysis and cross-correlation analyses were conducted on EEG signals. The authors noted that blue was associated with the highest complexity, followed closely by red, and they noted green as the lowest (noting previous literature noted green as the baseline). In addition, they reported that color stimuli decreased regional connectivity in brain regions, while gray backgrounds restored that connectivity. Thus, the authors observed that colors elicited wavelength-dependent modulation on cortical dynamics. Even though physiological and neurological mechanisms are the primary focus of such studies, the broader implications of color perception and individual variability should also be considered. In addition, several EEG studies have reported that color-related cortical responses vary not only with stimulus properties but also with individual perceptual and cognitive factors, further supporting the need to account for inter-individual differences in visual perception [5, 7].

Individual differences in visual perception are particularly evident when observers are presented with ambiguous visual stimuli. A well-known example is the “dress” illusion, which revealed striking inter-individual variability in color perception among healthy participants viewing the same stimulus [8, 9]. Such differences are thought to arise from variations in perceptual priors and assumptions about illumination rather than pathological or clinical factors [10, 11]. Accordingly, grouping participants based on their perceptual interpretations of ambiguous stimuli has been widely adopted in the literature as a valid approach to investigate neural and cognitive mechanisms underlying visual perception. Moreover, colors influence feelings and behaviors [12], and understanding these mechanisms is important in applied fields such as design, human–computer interaction, and safety. Color vision deficits can have an influence on daily life and safety. Examining the neurophysiological correlates of such perceptual variability using EEG provides a non-invasive means to explore how individual differences in visual interpretation are reflected in cortical activity.

Building on this background, the present study investigates EEG-derived features associated with individual differences in the perception of ambiguous color stimuli. EEG signals were recorded while participants were exposed to different color stimuli, and a range of features was extracted to examine color-induced differences in cortical activity. By focusing on feature-level EEG analysis, this study aims to provide a neurophysiological perspective on how individual perceptual interpretations of color are reflected in brain activity.

2. Materials and Methods

2.1. Participants and EEG recordings

The Neuron-Spectrum.NET system (NS4MEP model) was used to record EEG data with a Double Banana 19-channel montage (Figure 1). The sample rate was set to 1000 Hz. 18-Channel EEG signals were obtained, and the locations of the channels are given in Table 1. To remove slow drifts and high-frequency noise, a 0.5-Hz and 35-Hz bandpass filter was used, respectively. A 50 Hz notch filter was also employed to eliminate power line interference. Eye movement–related artifacts were manually identified by the recording operator through visual inspection and removed using the EEG acquisition system. EEG recordings were conducted at the Department of Electroneurophysiology, Halil Bayraktar Vocational School of Health Services, Erciyes University. The study was approved by the Erciyes University Health Sciences Research Ethics Committee under approval number 2025/186. All participants were informed about the study procedures and provided written informed consent prior to their participation. Participants aged 18–50 years with no history of neurological or visual disorders and capable of maintaining sustained attention were included in the study. Individuals with photosensitivity, color blindness, scalp conditions interfering with EEG recording, or regular use of central nervous system–affecting medication were excluded. Ten male and two female healthy volunteers (mean age 22.23, standard deviation 2.13) participated in the study.

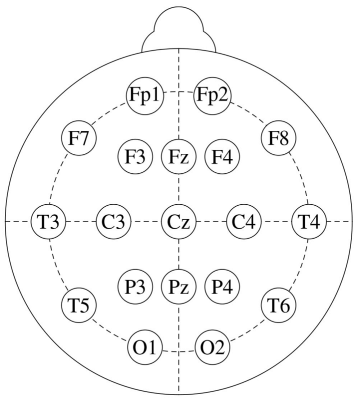


Figure 1. The standard 10–20 EEG electrode placements with 18 channels.

Table 1. EEG Channels

1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Fp1-F7	F7-T3	T3-T5	T5-O1	Fp1-F3	F3-C3	C3-P3	P3-O1	Fz-Cz
10	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
Cz-Pz	Fp2-F4	F4-C4	C4-P4	P4-O2	Fp2-F8	F8-T4	T4-T6	T6-O2

2.2. Experimental Design

In the experimental program designed for this study, EEG signals were recorded to examine changes in participants' brain activity in response to different colors. A total of eight colors (black, white, red, green, blue, yellow, cyan, and magenta) were presented sequentially. The test began with black, which served as the resting color. Each color was displayed for 20 seconds, followed by a 5-second black screen to minimize artifacts and improve signal quality between transitions. Thus, 195-second-long EEG signals were obtained for each participant. EEG recordings were obtained while participants viewed various color stimuli presented on a 24-inch LCD monitor, positioned 50 cm (±5 cm) away [5], as shown in Figure 2. The monitor brightness and contrast settings were kept constant for all participants and all color stimuli during EEG recordings. The experimental environment is quiet and slightly dark, so the volunteer will not be distracted and can focus solely on the colors on the screen.

After the color presentation phase, two additional visual stimuli (a dress and a shoe, Figure 3), whose colors appeared differently due to shading effects, were shown. Each participant observed two distinct color combinations of these images. Following the experiment, participants were asked to report the colors they perceived for both pictures. Based on their responses, those who identified the dress as blue–black and the shoe as turquoise–gray were labeled as Group 1, while participants who reported the dress as white–gold and the shoe as pink–white were labeled as Group 2. Thus, six participants were labeled as Group 1, and six participants were labeled as Group 2. EEG signals were segmented into epochs corresponding to the color stimulus presentation periods. The duration of each epoch was predefined and controlled using custom-developed Python-based software for stimulus presentation.

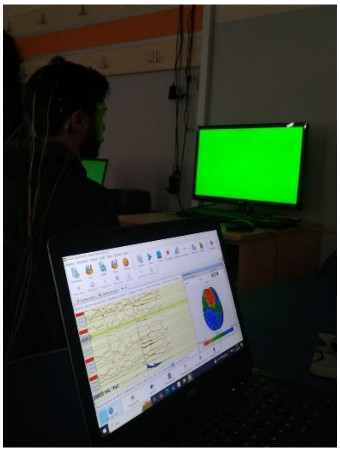


Figure 2. Experimental setup during EEG recording

a) b)

Figure 3. Ambiguous color stimuli used in the experiment: (a) the dress, and (b) the shoe.

Table 3. Features and brief descriptions

Name of feature	Description of feature	Formulization
Energy	Energy of a signal, returns the sum of the squares of the amplitude of a signal of length N.	Eq. (1)
RMS	Root mean square of the signal	Eq. (2)
Activity	Variation of the signal	Eq. (3), μ: mean
Mobility	measure of mean frequency	Eq. (4), X′ [n] denotes the first derivative of the signal, σ: standard deviation
Complexity	quantifies the signal's similarity to a pure sine wave	Eq. (5)
Wavelet Entropy	It is a metric that measures the irregularity of the frequency components obtained by applying wavelet transformation to the EEG signal up to a certain level (level 5).	Eq. (6), p denotes the probability density function, E_i indicates the normalized energy ratio of each wavelet sub-band. the 'db4' wavelet function and the 'shannon' entropy type were used.

Table 2. Labels for participants

P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
Group1	Group1	Group2	Group1	Group1	Group1	Group1	Group2	Group2	Group2	Group2	Group2

*P: Participant

2.3. Feature extraction

Six features, including energy, RMS (Root Mean Square), Hjorth parameters, and wavelet entropy values, were obtained from each channel of the EEG signals separately for all color stages. Hjorth parameters and entropy values are particularly important for examining differences in brain activity [13]. Brief descriptions of the features and their formulas were given in Table 3.

$$X_{energy} = \sum_{n=1}^{N} |X[n]|^2 \tag{1}$$

$$X_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} |X[n]|^2} \tag{2}$$

$$X_{activity} = \frac{\sum_{n=1}^{N}(X[n] - \mu)^2}{N} \tag{3}$$

$$X_{mobility} = \frac{\sigma(X'[n])}{\sigma(X[n])} \tag{4}$$

$$X_{complexity} = \frac{mobility(X'[n])}{mobility(X[n])} \tag{5}$$

$$X_{WEntropy} = -\sum_{i=1}^{N} p(E_i) log_2\,(p(E_i)) \tag{6}$$

2.4. Statistical analysis

Statistical analyses were conducted to examine differences in EEG-derived features between the two participant groups. Prior to hypothesis testing, data normality was assessed for each feature. For features that met normality assumptions, Independent Sample t-tests were applied. For features that did not follow a normal distribution, the non-parametric Mann–Whitney U test was used. Statistical significance was set at $p < 0.05$. Only features showing statistically significant differences between groups are reported in Table 4, whereas detailed statistical procedures and complete results are provided in the Supplementary File.

3. Results

In this section, statistical analysis of the features extracted from EEG signals, the differences between the two defined groups, and topographic EEG drawings are given. Table 4 presents the channel-based and color-based features that revealed significant differences between the two groups of participants, as determined by statistical analysis. For the indicated colors and channels, $p < 0.05$. When the results obtained in Table 4 were examined for all EEG channels, significant differences were found to be concentrated particularly in the temporal (T3–T5, F7–T3), parietal (C4–P4, Cz–Pz, P4–O2), and frontal (F4–C4, Fp2–F8) regions.

The Complexity and activity features provided the most significant differences between the two groups. This indicates that color stimulation causes noticeable changes in the complexity and activity levels of EEG signals. Significant differences were observed 14 times with the features obtained in the T3-T5 channel, and these differences occurred while viewing images of black, blue, and cyan colors. These findings suggest that brain responses to color stimulation are more pronounced in the frontal and temporal regions, and that cold (blue, cyan) and neutral (black, white) colors elicit greater differences compared to other colors. In the statistical analysis results presented in the supplementary file, for values with a p-value less than 0.05, that is, for values found to be significant, group statistics are provided as mean ± standard deviation for normally distributed data and as median (interquartile range, IQR) for non-normally distributed data.

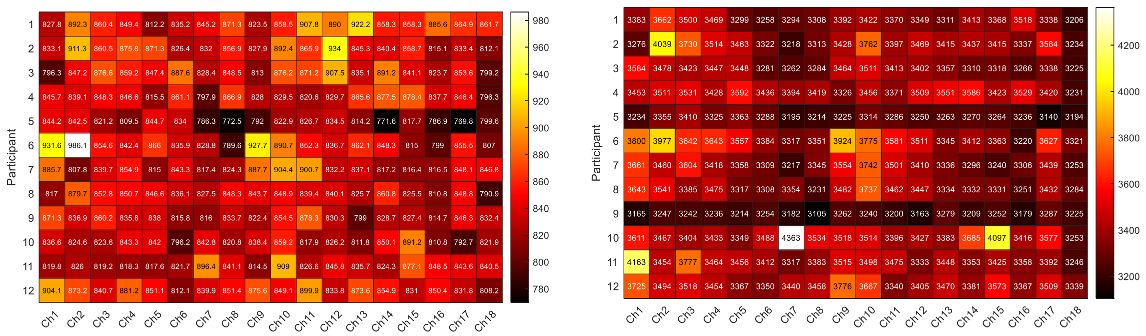
Table 4. Significant features according to channels

Ch.No	Channel	Energy	RMS	Activity	Mobility	Complexity	Wavelet Entropy	Fr.
1	Fp1-F7	-	-	-	-	-	-	0
2	F7-T3	black, yellow	black	black	-	-	black	5
3	T3-T5	Black, blue, cyan	black, cyan	black, cyan	Black, white	black, cyan	black, blue, cyan	14
4	T5-O1	-	-	-	-	black, white, yellow	-	3
5	Fp1-F3	-	-	-	-	-	-	0
6	F3-C3	-	-	-	green	-	-	1
7	C3-P3	-	-	black, red	-	-	-	2
8	P3-O1	-	-	-	-	-	-	0
9	Fz-Cz	-	-	-	-	-	-	0
10	Cz-Pz	-	-	black, white	-	black	-	3
11	Fp2-F4	-	-	-	-	black	-	1
12	F4-C4	-	black	black	white	white	black	5
13	C4-P4	black	-	black	black	Black, magenta, yellow	-	6
14	P4-O2	-	-	black	-	-	black	2
15	Fp2-F8	-	-	-	black	black	-	2
16	F8-T4	-	-	-	-	-	-	0
17	T4-T6	-	-	-	-	-	-	0
18	T6-O2	-	-	-	-	-	-	0
	Fr.	6	4	10	6	12	6	

*Ch. No. indicates the channel number. Fr. denotes the frequency of occurrence, representing the number of EEG channels in which the corresponding feature showed statistically significant differences between groups.

The heatmap shown in Figure 4 was generated based on energy values, as this feature provided the most visually distinguishable representation of differences between the two groups across cortical regions. Although other features, such as activity, showed statistical significance in a greater number of channels, energy was selected for visualization purposes due to its superior ability to highlight spatial activation differences between groups. Figure 4 shows the heatmap of the energy values of the EEG signals obtained while seeing the colors black and cyan, where the most significant difference between the groups is observed. The EEG energy values in black are significantly lower than those in cyan. Furthermore, participants 8-12 were labeled Group 2, and they reported seeing the dress as gold-white and the shoes as pink-white. The variation between the energy levels of these participants' EEG channels is greater.

Figure 5 shows that the effects of different color stimuli on EEG features for Channel 3 (T3-T5) varied depending on both participant groups and feature type. Specifically, for Wavelet Entropy, Energy, and RMS, Group 1 exhibited higher values than Group 2 for some colors (e.g., blue, red). The activity feature showed lower values for Group 1 than for Group 2 in all colors. For other features (Complexity, Mobility) differences between groups were more limited. These findings suggest that colors may have different effects on brain electrical activity and complexity across groups.



(a) **(b)**

Figure 4. Heatmap of energy values based on EEG channels: a) black color b) cyan color

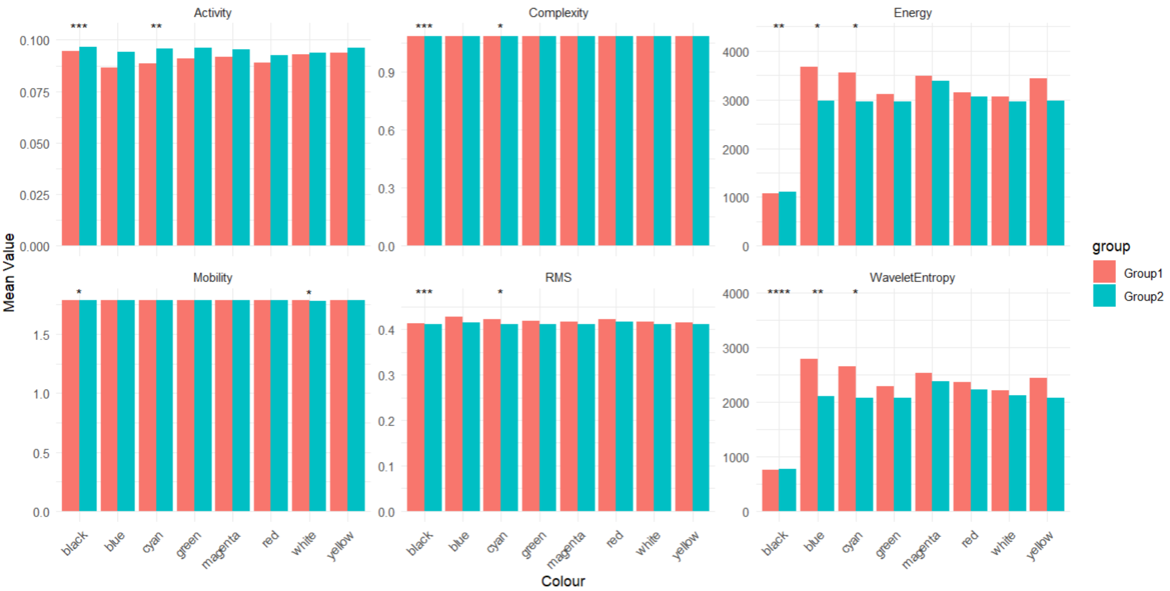


Figure 5. Mean values of EEG features under different color stimuli (for Channel 3, T3-T5): Comparison of Group1 and Group2. Statistical significance is indicated as * p < 0.05, ** p < 0.01, *** p < 0.001, **** p < 0.0001.

Figure 6 demonstrates the topographic brain activity distributions of EEG energy values in participants 4 and 12 in response to color stimuli. This enables us to observe how various colors influence brain activity for all subjects. Although participant 4 showed consistent activation across colors, participant 12 exhibited a significant increase in frontal and central areas, particularly to red and green. This suggests that color perceived can produce distinctive responses in the brain in addition to interindividual variation. Together, Figures 5 and 6 provide complementary perspectives on group differences in EEG responses to color stimuli. While Figure 5 highlights statistically significant differences at the feature level, Figure 6 offers a spatial visualization of how cortical activation patterns differ between groups across colors. This combined analytical and visual approach enables a more comprehensive interpretation of both quantitative and neurophysiological aspects of the findings.

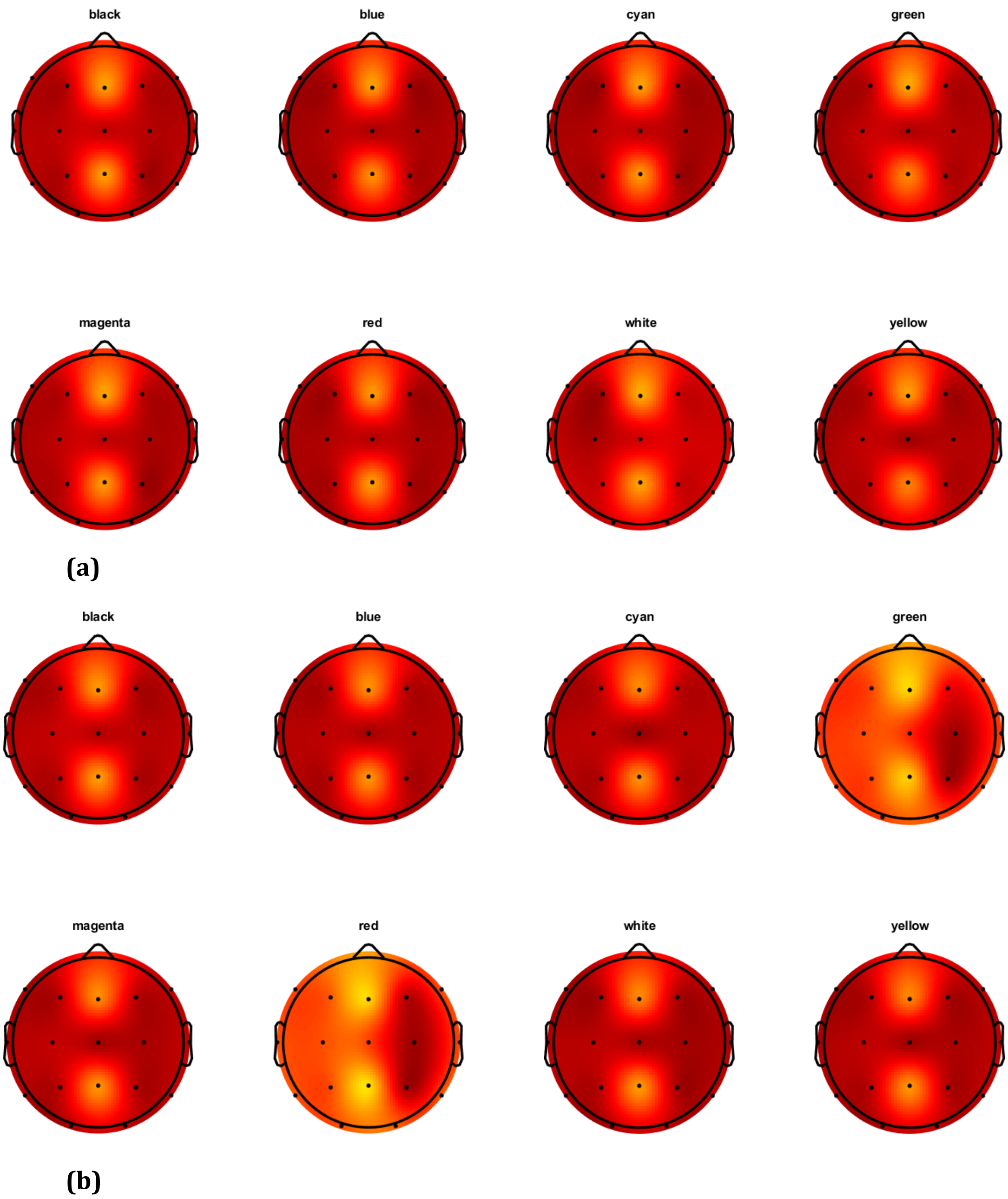


Figure 6. Brain Activity Distribution According to Color Stimuli; a) Participant-4 (Group1), b) Participant-12 (Group2)

4. Discussion

The capacity to perceive colors involves a complex deployment of neural processes, commencing in the retina and extending into multiple brain areas. This process involves the interaction of photoreceptor cells in the retina and the pathways in the brain that process this information [14]. The interaction of these systems plays a large role in the detection and treatment of disorders involving color vision. Roughly one-fifth of the human brain is involved with the visual cortex, which includes the occipital lobe and extends into the temporal and parietal areas of the brain [1]. In recent years, there has been increasing interest surrounding the effects of visual stimuli in EEG signals, especially when related to brain-computer interface (BCI) systems. The majority of studies examine cognitive effects of colors on brainwaves utilizing combinations of signal processing and machine learning techniques. For example, Khadir and Beigzadeh [15] demonstrated that black-and-white and RGB stimuli produced different alpha and beta activity in the occipito-parietal and centro-parietal areas, and that the RGB stimuli induced different brainwave effects in both the early and late response of visual processing.

Chai et al. [16] reported in their study that colored learning materials enhanced emotional state and memory performance, evaluated through EEG connectivity networks. Specifically, warm and cool colors affected the information flow and long-term recall differently. Mathur et al. [17] showed that deep learning-based classifiers allow for an accurate discrimination between iconic memory and visual working memory stages by using EEG signals.

In studies involving the classification of EEG signals based on color, Alharbi et al. [18] achieved around 97% accuracy on RGB stimuli with an EMD feature selection and SVM classification. Garcia and Monilas [19] noticed they were able to separate both real and imagined colors with EEG and reported that the alpha and beta bands in the frontal and occipital areas were of particular importance and some participants demonstrated more marked EEG responses to red and yellow and in both conditions, perceptually and imagined. These results indicate responses can differentiate between externally perceived colors and colors imagined internally EEG responses, and these EEG based systems support neuroscience, attention training, and visual applications in BCI. Sun and Gao [20] clearly demonstrated using frequency tagging that color categories entered representations during very early stages of visual processing, within roughly 300 ms. Roy et al. [6] demonstrated visual colors produced differential EEG complexity and differential inter-lobe correlation in EEG with blue showing the greatest multifractal width. Hajonides et al. [21] demonstrated visual colors can be represented with EEG, and chromatic differences can be more accurately predicted than luminance. Rakshit and Lahiri [22] improved on the previous work and expressed and classified colors, the four basic colors, using EEG and obtained up to 85% accuracy using the IT2FS classifier.

The results of the studies performed on inter-eye color fusion and rivalry highlighted the complex role of the occipital channels and the necessity for an individual-specific model [23]. Khadir et al. [4] indicated that RGB stimuli exhibit differential beta and theta activation in the occipital and prefrontal regions, which may provide potential markers for spatiotemporal color processing.

The results of these studies therefore favor the hypothesis that visual color stimuli provoke unique patterns of cortical activation that vary both with color category and across subjects. The complexity parameter turned out to be the most sensitive across all conditions, reflecting the complex character of neural dynamics during visual processing. Complexity is commonly associated with increased neural integration and signal irregularity, which have been linked to higher cognitive load and perceptual uncertainty in tasks involving ambiguous sensory processing [24, 25]. Accordingly, the observed increases complexity in this study may reflect enhanced cortical integration mechanisms engaged during the processing of visually ambiguous color stimuli. Warm tones-e.g., red, yellow, and magenta-presented with extended frontal-parietal activations, whereas cool tones, like blue and cyan, elicited more spatially focused and symmetric occipital responses. These differences in topography indicate that emotional and perceptual components jointly determine cortical responses. Further, there were also interindividual differences in the topographic maps: several participants showed clear lateralization, while others had midline-centered activity. This could imply that color perception and cortical processing are variable across individuals and might be due to differences in visual pathways or attentional mechanisms. Sensitivity in occipital-parietal and frontal regions supports the idea of distributed networks involved in color-related processes of cognition.

Several EEG studies investigating visual perception and color processing have primarily focused on feature level and group-wise neurophysiological differences rather than classification performance, particularly in exploratory or pilot settings. Previous studies have emphasized that classification-based approaches in EEG research require sufficiently large and balanced datasets to ensure reliable and generalizable results, whereas small-sample studies are more appropriately suited for hypothesis generation and neurophysiological interpretation rather than predictive modeling [26, 27]. In line with this perspective, the present study prioritizes the analysis of EEG-derived features to elucidate cortical responses to color stimuli, while classification-based modeling is intentionally reserved for future work involving larger participants.

Despite its contributions, the present study has certain limitations that should be acknowledged. Although gender-related differences in EEG have been reported in certain cognitive and emotional tasks, existing literature suggests that gender is not a primary determinant in early visual color processing, but rather a secondary modulating factor [2]. Although the sample size is limited (n = 12), this study was designed as a preliminary investigation. Similar EEG studies investigating color perception and visual processing have been conducted with comparable or even smaller sample sizes (e.g., Roy et al. [6], n = 16; Torres-García and Molinas [19], n = 7; Rakshit and Lahiri [22], n = 7; Alharbi et al. [18], n = 16; Lv et al. [23], n = 10). Therefore, the present sample size is consistent with the exploratory nature of EEG-based neurophysiological studies. Another limitation of the present study concerns the assessment of the temporal stability of perceptual responses to ambiguous visual stimuli. Although participants' perceptual responses to the ambiguous dress and shoe images were reassessed at the end of the EEG recording session and no notable changes were observed, perceptual responses were not continuously monitored throughout the experiment. Therefore, potential temporal fluctuations in perceptual interpretation could not be fully captured and should be addressed in future studies.

5. Conclusion and future directions

This research investigated the use of EEG signals to show the activity of the brain regions associated with different colors. Specifically, it showed that, relative to other colors, the EEG signals revealed quite a bit of difference across each color, with complex EEG signals revealing cool colors had more activity in the occipital brain regions relative to warm colors, while warm colors had higher activity in the frontal and parietal regions. The results demonstrate that visual stimuli produce brain-specific, distinct, dynamic effects and that there are unique brain activity differences between colors. This research included a small sample size and used short-term visual stimuli during the EEG readings, which limits the generalizability of the findings. Future studies plan to support these findings using larger samples, different color intensities and durations, and multimodal approaches such as eye tracking and fMRI. Furthermore, modeling color-based EEG patterns with artificial neural networks will significantly contribute to understanding individual differences in visual perception.

Peer-review: External, Independent.

Acknowledgements:

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Declarations:

1. Statement of Originality:

This work is original.

2. Author Contributions:

Concept: ÇGA,TD,FK,AC; ***Conceptualization:*** ÇGA,TD,FK,AC; ***Literature Search:*** ÇGA,TD,FK,AC; ***Data Collection:*** EE,TD,FK,AC; ***Data Processing:*** EE,TD,FK,AC; ***Analysis:*** ÇGA,TD,FK,AC; ***Writing – original***

draft: TD,FK,AC; ***Writing – review & editing:*** ÇGA,EE.

3. Ethics approval:

This study was conducted by the Erciyes University Health Sciences Research Ethics Committee under approval number 2025/186.

4. Funding/Support:

This work has not received any funding or support.

5. Competing Interests:

The authors declare no competing interests.

6. GenAI Usage Statement:

No GenAI tools were used at any stage of the study.

7. Sustainable Development Goals:

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