Interpreting emotions with EEG: an experimental study with chromatic variation in VR

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also their perception and emotions during and after an interaction with a product, system, or service.

Emotions are often described as feelings concerning a specific phenomenon, such as a mood or a sentiment. Many studies have used almost exclusively self-report measures to study the users' emotions; however, technological advances can make other kinds of measurement more plausible. For example, self-reported measures can be contrasted to other experimental methods that do not rely only on respondents' reports, for example, physiological approaches that can measure respondents' behaviors in a constrained or controlled environment. The inclusion of physiological parameters provides information that allows the researcher to determine whether the findings from self-reports are trustworthy and representative to find the "ground truth" of the emotion [3].

Electroencephalography (EEG), a technique for recording and interpreting the brain's electrical activity, could be a promising tool to measure user emotions. By analyzing EEG data during users' exposition to a stimulus, studies have shown that EEG can provide metrics for determining different emotional traits and indicators [4, 5]. Concerning emotions, empirical studies have confirmed that colors and environment design might evoke positive or negative feelings and influence users' moods and emotions [6, 7]. This study explores the EEG as a method for emotion interpretation using chromatic and scenario changes as the stimulus. To do this, we have created three different VR scenarios characterized by different interior designs: an open space living room, an industrial loft, and an outdoor environment, all of them with lighting color changes, passing through white, yellow, orange, red, violet, blue and green. This study aims to explore whether this stimulus variation can evoke an emotional response affecting the users' perceptions.

1.1 The representation of emotions

Emotions allow us to relate to other people and express our behavior towards others and our environment. The emotional response can be caused by several factors that stimulate us, such as a behavioral factor or an automatic response. To explain these concepts, Russell [8] developed the circumplex model of affect (Fig.1), a 2D emotion space structured to express emotions through two dimensions: Valence and Arousal.

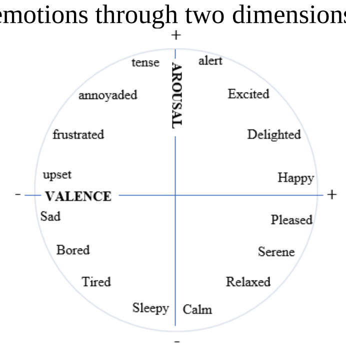

Fig. 1. Circumplex model of affect

Arousal expresses the intensity of the emotion (ex. more or less calm or agitated), and Valence is the level of pleasantness or unpleasantness concerning a perceived stimulus. Furthermore, User Engagement (UE), a typical emotion in the context of human-computer interaction, has been a matter of interest for enabling interfaces to adapt to users [9]. It can be interpreted as the level of involvement and absorption into an activity. It can give us further information for analyzing the users' perspective during the product interaction. In particular, cognitive Engagement reflects the idea of mental workload and willingness to execute a task [10].

1.2 Overview of the color influence and EEG emotions interpretation

The literature shows that the chromatic influence of the colors is still a matter of research; authors have explored how colors have stimulating capacities of excitement for warmer shades or calming ones for colder ones [11]. In a recent study [12], the authors proposed a methodology for creating VR environments oriented to elicit emotions and stated that bright saturated colors are usually related with high Valence and Arousal, less saturated colors with calm, and in particular red color can be associated with angry. Likewise, similar studies have concluded a significant variation while changing scenarios typology [7], a greater level of emotional pleasure in the more colorful work environments [11], and different emotional relationships according to the color analyzed. Disgust prevailed in the color red; happiness was the emotion widely expressed for the green, while in the blue, the reactions remained neutral [6].

Regarding the use of EEG for emotion interpretation, studies have shown that EEG can provide metrics for determining task Engagement, Valence, Arousal, and other indices useful to understand human behavior. McMahan et al. [4] compared three different Engagement indices during videogames play using an EEG system. They concluded that EEG could measure the users' level of Engagement while playing, and suggested according to their findings, the most suitable index to use for future studies. In addition, the authors identified the need for further validation by exploring and analyzing this methodological approach in other research fields.

Suhaimi et al. [13] performed an EEG study for measuring the participant reactions to visual stimuli intended to provoke different emotions. After each stimulus, they asked the participants to fill out a self-assessment questionnaire and collected EEG data for posterior correlation and classification. Similarly, Hu et al. [14] aimed to correlate ten emotions using a self-report questionnaire and EEG; the authors, however, recognized the subjectivity of the participant self-assessment, concluding that this is still an open scenario for research. Also Ramirez et al. [15] have conducted studies to analyze the effects of music during health treatments; in these studies, the authors have computed and validated the Valence and Arousal indices for obtaining information about the patient's emotional state. Finally, the systematic review by Ismail and Karwowski [16] can be considered a valid synthesis of the EEG indices and trends used for measuring human cognitive performance.

Although there have been advances in research in this field, many of these studies have been conducted using self-assessment reports as a means to evaluate the users' responses, which, despite being an agile and supportive tool, rely solely on the answers consciously indicated by the evaluated subject, tending to subjectivity and a lack of validation of the user's primary emotional response [7,13,14]. In this way, there is an open opportunity to investigate EEG to attain quantitative results in fields related to engineering and design. This study aims to close a gap derived from the literature, which sustains that the colors can elicit an emotional response, although it has been evaluated mainly through questionnaires, and that EEG can be used to monitor the user's emotions, but there is still the need to expand the EEG validation to other fields. This study contributes to the emotional design research by analyzing the users' responses to colors using a physiological method (EEG), exploring the EEG analysis's pertinence for product design and development, and complementing the findings obtained from previous studies.

2 Methods

This study aims to explore EEG as a method for emotion interpretation through the analysis of Valence, Arousal, and Engagement indicators, during the exploration of three VR environments characterized by color changes (white, yellow, orange, red, violet, blue and green) and different design style (open space, industrial loft, and outdoor).

2.1 EEG as a physiological tool for understanding users' emotions

EEG is a technique for recording and interpreting the brain's electrical activity. According to the user's situation, the brain's nerve cells generate electrical impulses that fluctuate rhythmically in different patterns. This study was conducted using the Emotiv EPOC+, a mobile EEG Instrument composed of 14 saline-based electrodes located according to the international 10-20 sensor placement system.

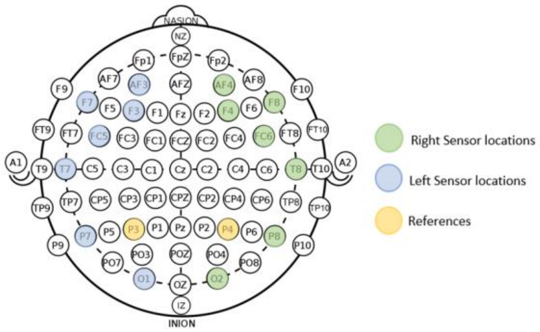

Fig. 2. Sensor locations

The sensors are at positions AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2, and two additional CMS/DRL reference channels (Fig.2) at P3 and P4. The sampling rate is 128Hz, and the bandwidth is 0.2 - 45Hz.

The electrical EEG signal is composed of different frequencies produced by neuronal electrical activity; these frequencies, known as bands, are classified as Theta (θ) (4–8 Hz), Alfa (α) (8-12 Hz), Beta (β) (12-25 Hz), and Gamma (γ) (25-45 Hz). Each type of band reflects specific and different cognitive processing skills in specific areas of the brain [17]. The theta (θ) waves are associated with lower mental activity or meditative states; the alpha (α) waves are related to relaxation and usually appear in a sleep-wake cycle. In contrast, the Beta (β) waves describe a system activation and alertness, and Gamma (γ) waves learning and information processing.

Alpha (α) waves are associated with calmness and relaxing states, and also, they have been related to brain inactivation. Beta (β) waves are dominant when attention is directed towards a task or when a person is alert and engaged in mental activity. Hence, the beta/alpha power ratio is considered an appropriate indicator of the Arousal state [18, 19]:

$$Arousal = \frac{\beta F3 + \beta F4}{\alpha F3 + \alpha F4}. \quad (1)$$

Additionally, EEG studies have shown that the right brain hemisphere is dominant for negative or unpleasant emotions and that the left hemisphere is dominant for positive or pleasant emotions [15]. It has been suggested that it is an indication of motivational direction. Thus, for analyzing Valence, this study used the frontal alpha (α) asymmetry index to evaluate the hemispherical activation in the frontal lobe related to emotion regulation (sensors F4 and F3) [20] by subtracting the natural log of the left hemisphere alpha power (αF3) from the natural log of right hemisphere alpha power (αF4) and comparing their difference:

$$Valence = \alpha F4 - \alpha F3. \quad (2)$$

Since alpha (α) power is inversely related to regional brain activity, decreased power values of the alpha (α) band indicate an increase in cortical activation, so higher scores in equation 2 indicate relatively greater left frontal activity (increased Valence) and lower scores relatively greater right frontal activity (decreased Valence) [21]. Similarly, higher scores in equation 1 indicate an increase in Arousal states.

In the study carried out by Freeman et al. [22], the authors validated the EEG Engagement index (equation 3). Considering that Beta (β) power is related to an increase in brain activity during mental tasks, and alpha (α) and theta (θ) activity are related to lower mental vigilance (theta (θ) brainwaves occur most often in sleep), using this index, it is possible to identify the Engagement by comparing the initial state with a post stimulus response; if it increases, a higher Engagement and sustained attention is expected.

$$Engagement = \frac{\beta}{\alpha + \theta}. \quad (3)$$

In this study, each participant's Engagement index was calculated using the averaged measurement from all sensors.

2.2 Data analysis and feature extraction

For data analysis, a bandpass filter and Fast Fourier Transformation was performed, the band power (μV^2) calculation was done at 0.125-second intervals (8Hz). A Hanning window was applied to reduce noise artifacts from the FFT procedure. And the squared magnitude of the complex FFT value was averaged across the frequency bins in each band. For emotional metrics assessment, the equations 1, 2, and 3 were employed. For Valence and Arousal, EEG data was analyzed in 4 locations on the prefrontal cortex: AF3, AF4, F3, and F4.

It is important to highlight that there are no absolute maximum or minimum levels for Arousal, Valence, and Engagement since these values vary from person to person. For this reason, this study used a "within-subject design" experiment commonly employed in the EEG research field [23, 24]. As well as in other physiological methods (ex. GSD and heart rate), the EEG measurement is divided into two phases; the first one consists of baseline data to control the initial subject response, and the second containing the electrical brain activity measurement while carrying out a task (stimulus). By comparing the difference between the baseline and the stimulus during the experiment, it is possible to identify the activation response and, therefore, the increase/decrease of the emotional metrics [20].

2.3 Experiment setup

Recent studies have established the potential of VR to elicit emotions by creating multisensorial and interactive environments [12]; however, despite the exponential increase of implementation of VR in different fields, studies relating to EEG-based emotional classification are not commonly researched using VR as the stimulus [13]. Therefore, considering the possibilities that VR applications can give to the emotional analysis and that EEG used simultaneously in VR experiments is still an open research opportunity, we wanted to create an immersive experience for the participants and explore the EEG for emotion monitoring. Specifically, this research used the VR environments as an interactive context in order to analyze with the EEG if the color variations in the scenarios might or might not elicit emotional responses, as previously claimed by studies that used only self-reports. In this sense, the objective of the study is to explore the EEG as a method for detecting and monitoring the emotional responses elicited by color variation through the analysis of Valence, Arousal, and Engagement quantitative indicators.

The study conducted by Dozio et al. [12] provides a guideline for the creation of affective VR scenarios. According to these suggestions, our compositions included natural and concrete elements like mountains, forest and furniture, as well as abstract elements, including chromatic variation, which is the specific interest of this study. In order to vary over the broadest possible spectrum to elicit emotions, we have created three VR scenarios characterized by different architecture styles (an open space apartment, an industrial loft, and an outdoor space) and added visual elements that include the use of colors, lighting, and forms, to express the time of the day (dark or bright) and the weather. Within each of the scenarios the colors selected for this work (white, yellow, orange, red, violet, blue and green) vary according to the environment's chromatic lightning, which changes every 30 seconds. The VR scenarios were conceived to create three-dimensional neutral and aesthetically pleasing environments. They were designed and created using Blender 2.92 and then exported to Unity.

Open Space. The first VR scenario (VR1) was designed to be bright and structured as a home. The surrounding space and the view are composed of a large sliding window, from which the user will see a sunny day with few clouds and a vast blue sky.

Industrial Loft. The second (VR2) is darker and less bright; the view faces other urban buildings. It is a gloomy day with pouring rain and poor external visibility.

Outdoor. The third VR scenario (VR3) consists of a natural oasis in the middle of a desert; the shapes and spaces are minimalist, there are no walls that delimit the areas, but a natural and free space. It is a peaceful night with a starry sky.

Our study consisted of a controlled experiment (Fig. 3) carried out in a laboratory setting with 34 healthy participants, 14 women (41%) and 20 men (59%), aged between 20 to 30. All participants were informed about the experiment, the protection and use of their data, and were given an informed consent to sign. Then, each participant went to a closed room, equipped with a comfortable chair, screen, and controls to move across scenarios. All the participants (one at a time) executed the test in the same room. After the helmet setting up, the initial baseline was recorded, and the lights were turned off to facilitate the immersion and adequately run the experiment.

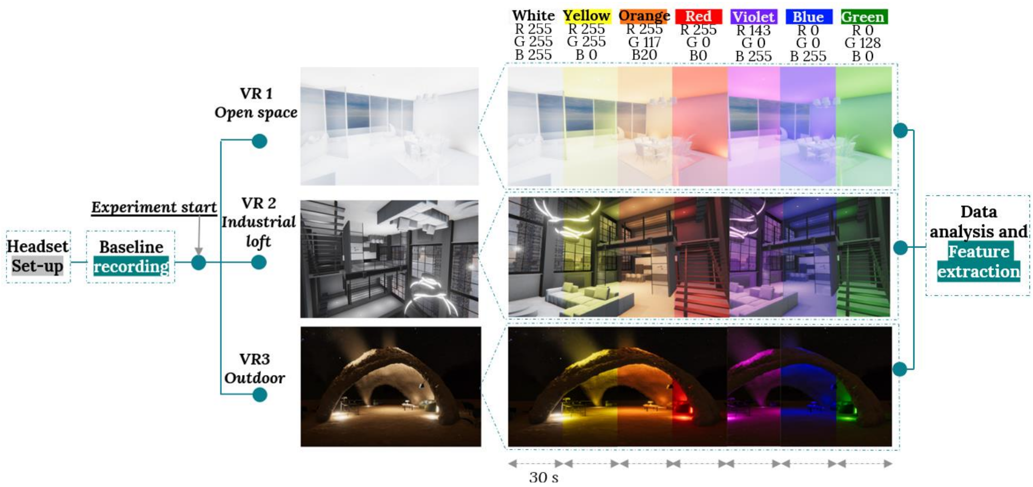

Fig. 3. Experiment setup. The first two scenarios are in daytime, the first set in a sunny day, the second in a rainy one. The third scenario is set at night-time.

Each user was asked to explore the three scenarios freely while measuring their brain activity with the EEG headset. In each scenario, there was a color change every 30 seconds. The test was carried out without interruptions between changes of scenarios and colors. At the end of every stage, an automatic marker was placed. The total duration of the experiment is about 12 minutes plus the headset setting time.

3 Results

The data was processed and found artifacts were removed. From the sample of 34 participants, only 30 results were considered valid for the purposes of this study. The EEG data were segmented into 30s epochs according to the color stimulus interval and scenario. Then for each participant, the emotional indicators (Arousal, Valence, and Engagement) for each scenario and color were extrapolated from the EEG data. The baseline data was extracted and then subtracted from the post-stimulus response; in this way, it was possible to analyze the contribution of the individual stimulus to the emotional response. To avoid skewness [25], the median was analyzed to measure the central tendency of our data set. Considering the entire color contributions as a whole and comparing only the variation of scenarios (Fig. 4a), from the examination of global values, it emerged that the Engagement was higher in the VR3, a natural oasis with no walls delimiting the areas, and lower in the VR2, an urban building in a raining day, while in the VR1, an open space living room, the Engagement barely increased. The Arousal was equivalent in the VR1 and VR3 but decreased in the VR2, while the Valence gradually decreased as long the test was carried out. These results could suggest that the weather and lighting conditions affected the participants' Arousal also that the lack of visible spatial limits could increase the task Engagement. Moreover, Valence decrease could be related to boredom or tiredness. Considering the color changes (Fig. 4b), the findings show that the more engaging colors are white and red, followed by yellow, violet, and blue. At the same time, orange and green contributed to an Engagement decrease (computing the responses from all scenarios). Overall, there is a common increase of Valence, Arousal, and Engagement in the center segment of the test, suggesting that the users feel comfortable with the VR interaction and exploration. The median values of Arousal and Engagement are higher at the beginning of each test, indicating interest and curiosity for interacting with the environment for the first time. Similar to Fig. 4a, Valence decreases near the end of the test as people get used to the environment.

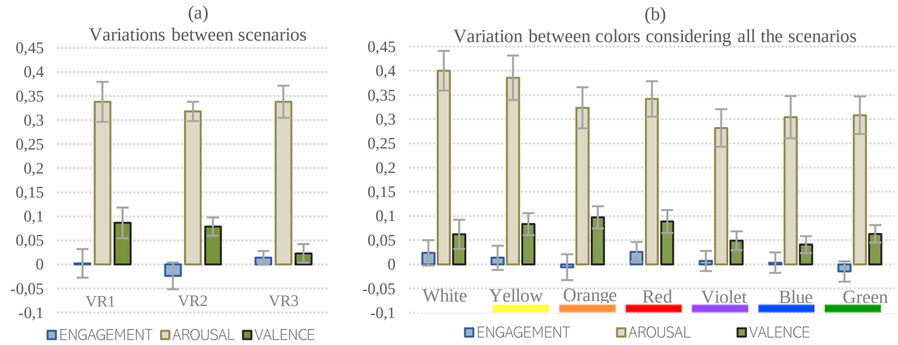

Fig. 4. (a) Variations between scenarios **(b)** Variations between colors. SD are shown for each condition. Highest SD=0,046 for Arousal in Yellow, and lower SD=0,017 for Valence in Blue.

4 Discussion

By reporting our outcomes to the circumplex model of affect (Fig. 5), it is possible to visualize that white and yellow have the highest Arousal values, and violet and blue the lowest. Related to Valence, red, yellow, and orange reported the most significant values, while blue the lowest, these findings are coherent with the warm and cold colors theory described by Kuller et al.[11], suggesting that warm colors like red, yellow, and orange are related to stimulating emotions, while cold colors such as blue, violet, and green are considered more relaxing.

Analyzing the specific color contributions inside each VR scenario, the findings show that the Arousal was high for all scenarios at the beginning of the test; this could be explained by the fact that this was the very first contact with the VR environments for the participants. On the other hand, the Valence has an increase in the middle section, and then it tends to decrease; the Engagement has a similar tendency, decreasing as the experiment was executed, although this is not explicitly related to the stimuli but to the test length. This result is aligned with the global analysis, suggesting that, even if the Arousal was always positive, the Valence and Engagement are inversely proportional to the test duration. The duration of the test in this type of study can act as a limitation, although an adequate amount of data is necessary for the correct analysis of the information, tests that are too long (according to the objective of the experiment) can affect the results, in our case a 12-minute test reported in the last 2 minutes a reduction of concentration and interest.

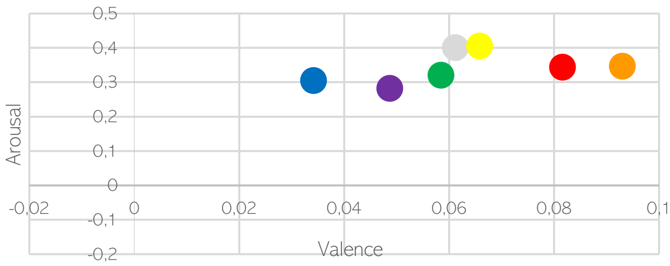

Fig. 5. Color stimulus circumplex model of affect

From all scenarios, VR1 (Fig.6a) reported the highest values of Arousal and Engagement, with a decreasing point in the violet and blue; indeed, these colors reported a negative Engagement, meaning that the participants lost interest at that point, however the green enhanced Engagement again. In the case of VR2 (Fig.6b), the Valence reached a peak in the violet colors, the Arousal was lower than at the beginning, and the Engagement was negative, remembering that the task Engagement is related to focused energy, cognitive activity, and attention, the behavior could mean that the participant was comfortable and relaxed but lost concentration. A similar behavior is recorded for the orange color.

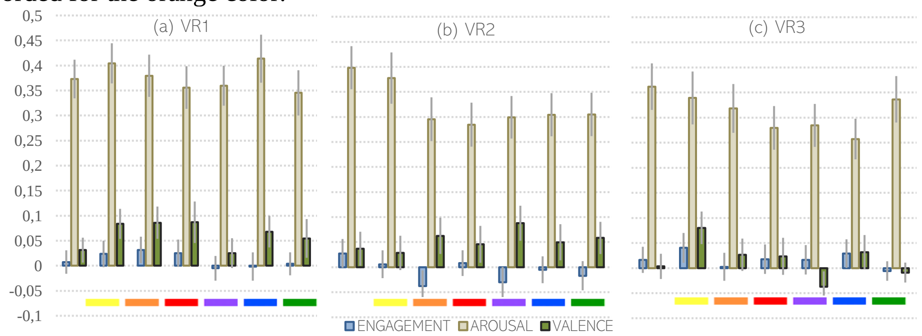

Fig. 6. Color variations **(a)** VR1 Open Space, (**b)**VR2 Industrial loft, **(c)** VR3 Outdoor. The color

tags at bottom indicates the color analyzed. SD are shown for each condition. Highest SD=0,048 for Arousal in Blue VR1, and lower SD=0,019 for Engagement in Green VR3.

Interestingly, the red color in VR2 caught the participant's attention, with a slight decrease of Valence but raising the Engagement again; this result validates the statement of Dozio et al. [12], indicating that red color can be associated with a state of alertness. The last scenario, VR3 (Fig.6c), reported the highest global Engagement of all but the lowest Valence. More organic colors, such as red, yellow, and orange, resulted in positive Valence, Arousal, and Engagement; in contrast, lighting conditions using unnatural colors or colors not considered typical of this environment (ex. violet light in a desert) caused a drop of Engagement. The comparison between the last color of VR3 (corresponding to the last section of the entire test) with the beginning of the experiment indicates a positive Arousal (same for all VR) and a lower Engagement and Valence. This finding means that the participant, during the entire experiment, experienced enthusiasm for participating but also, in the end, began to feel tired and distracted.

Comparing the results of our experiment with the findings of Stone [7], there are some similarities related to the environmental changes; even if the chromatic variations reported interesting results, the emotional responses were more evident when changing between scenarios. The differences between scenarios' nature, lighting conditions, weather, and spatial limitations prevailed over the chromatic variation exhibited. For instance, the Arousal was higher in the brightest scenarios designed to experience good weather conditions. Regarding the Engagement (an indicator used mainly in the video-games field and less studied in chromatic studies), the space design was impactful too; in the outdoor VR scenario the Engagement was significantly higher than in the closed spaces. The Valence showed a behavior similar to the Engagement; in general, it was always positive, with an evident growth in the non-extreme stages of each VR scenario interaction.

Our findings obtained through EEG analysis are coherent with those recorded in previous studies using qualitative approaches [7, 11, 12], proving that EEG can provide reliable quantitative information to improve the emotional analysis and to frame users' feelings and perceptions.

5 Conclusions

Getting to know the user perceptions towards a product can influence the direction of the design and increase the chances of success. As a result, the implications of the emotional analysis within the scope of the product/service design and development have recently been a matter of interest. Traditional methods have commonly used self-assessment metrics that often lead to subjective results. Therefore, the goal of this study was to explore the interpretation of emotions using a physiological tool, specifically Electroencephalography. To do this, and investigate if the colors variation could elicit an emotional response, three different Virtual Reality environments with chromatic variations of lighting were developed. The study employed a portable EEG headset to record the subject data during the experiment.

The main findings of this study are related to the validation of the EEG as a method for interpreting emotions by endorsing some results obtained in the previous literature based on questionnaires. The results show that the EEG outcomes are coherent with the theory of colors, and provide tangible results to support the emotional analysis research field aiming to eliminate personal bias (a consequence of the traditional self-assessment methods). Similarly, this research presents an example of the use and validation of emotional EEG quantitative indicators in a new field, contributing to fulfilling an existing requirement expressed in previous studies. Our results show that EEG can be used to analyze and determine the users' emotional states and that it can be employed along with traditional methods to avoid subjectivity in the responses. Also, physiological methods can provide additional information for the product development process, enhancing success possibilities. Finally, VR technologies combined with other experimental tools are a prominent method for product/services development and evaluation.

According to the literature, no previous studies have analyzed the influence of colors on emotions using EEG and VR. We expect this explorative study can be used as a starting point for a new approach for product design and development. In this research, VR acted as an interactive and support instrument, and the perimeter of this investigation was limited to the EEG analysis for emotion interpretation. Therefore, the impact of the VR representations on the perception of emotions with respect to a real scenario is not part of this study. However, we consider this limitation an open window for future research using EEG instruments and VR for emotional design.

References

1. Hekkert, P.: Design aesthetics : principles of pleasure in design Design aesthetics : principles of pleasure in design. Psychol. Sci. 48, 157–72 (2006).
2. Norman, D.A.: Emotional design. Basic Books, New York (2004).
3. Marcolin, F., Torino, P., Scurati, G.W., Milano, P., Nonis, F., Vezzetti, E., Torino, P., Milano, P.: Affective Virtual Reality : How to Design. 171–78 (2021).
4. McMahan, T., Parberry, I., Parsons, T.D.: Evaluating Player Task Engagement and Arousal Using Electroencephalography. Procedia Manuf. 3, 2303–10 (2015).
5. Lyu, Y., Honkanen, M.: Emotiv Epoc + live metrics quality validation. (2011).
6. Güneş, E., Olguntürk, N.: Color-emotion associations in interiors. Color Res. Appl. 45, 129–41 (2020).
7. Stone, N.J.: Designing effective study environments. J. Environ. Psychol. 21, 179–90 (2001).
8. Russell, J.A.: A circumplex model of affect. J. Pers. Soc. Psychol. 39, 1161–78 (1980).
9. Oertel, C., Castellano, G., Chetouani, M., Nasir, J., Obaid, M., Pelachaud, C., Peters, C.: Engagement in Human-Agent Interaction: An Overview. Front. Robot. AI. 7, 1–21 (2020).
10. Charland, P., Léger, P.M., Sénécal, S., Courtemanche, F., Mercier, J., Skelling, Y., Labonté-Lemoyne, E.: Assessing the multiple dimensions of engagement to characterize learning: A neurophysiological perspective. J. Vis. Exp. 2015, 1–8 (2015).
11. Küller, R., Mikellides, B., Janssens, J.: Color, arousal, and performance - A comparison of three experiments. Color Res. Appl. 34, 141–52 (2009).

12. Dozio, N., Marcolin, F., Scurati, G.W., Ulrich, L., Nonis, F., Vezzetti, E., Marsocci, G., La Rosa, A., Ferrise, F.: A design methodology for affective Virtual Reality. Int. J. Hum. Comput. Stud. 162, (2022).
13. Suhaimi, N.S., Yuan, C.T.B., Teo, J., Mountstephens, J.: Modeling the affective space of 360 virtual reality videos based on arousal and valence for wearable EEG-based VR emotion classification. Proc. - 2018 IEEE 14th Int. Colloq. Signal Process. its Appl. CSPA 2018. 167–72 (2018).
14. Hu, X., Yu, J., Song, M., Yu, C., Wang, F., Sun, P., Wang, D., Zhang, D.: EEG correlates of ten positive emotions. Front. Hum. Neurosci. 11, (2017).
15. Ramirez, R., Planas, J., Escude, N., Mercade, J., Farriols, C.: EEG-based analysis of the emotional effect of music therapy on palliative care cancer patients. Front. Psychol. 9, 1–7 (2018).
16. Ismail, L.E., Karwowski, W.: Applications of EEG indices for the quantification of human cognitive performance: A systematic review and bibliometric analysis. (2020).
17. Chaouachi, M., Frasson, C.: Exploring the Relationship between Learner EEG Mental Engagement and Affect. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). pp. 291–93 (2010).
18. Ramirez, R., Vamvakousis, Z.: Detecting emotion from EEG signals using the Emotive Epoc device. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics). 7670 LNAI, 175–84 (2012).
19. Giraldo, S., Ramirez, R.: Brain-Activity-Driven Real-Time Music Emotive Control. In: Luck, G. and Brabant, O. (eds.) ICME3 International Conference on Music and Emotion. pp. 11–15. , Jyväskylä, Finland (2013).
20. Coan, J.A., Allen, J.J.B.: Frontal EEG asymmetry as a moderator and mediator of emotion. Biol. Psychol. 67, 7–50 (2004).
21. Zhao, G., Zhang, Y., Ge, Y.: Frontal EEG asymmetry and middle line power difference in discrete emotions. Front. Behav. Neurosci. 12, 1–14 (2018).
22. Freeman, F.G., Mikulka, P.J., Prinzel, L.J., Scerbo, M.W.: Evaluation of an adaptive automation system using three EEG indices with a visual tracking task. Biol. Psychol. 50, 61–76 (1999).
23. Apicella, A., Arpaia, P., Mastrati, G., Moccaldi, N.: EEG-based detection of emotional valence towards a reproducible measurement of emotions. Sci. Rep. 11, 1–16 (2021).
24. Darfler, M., Cruz-Garza, J.G., Kalantari, S.: An EEG-Based Investigation of the Effect of Perceived Observation on Visual Memory in Virtual Environments. Brain Sci. 12, 269 (2022).
25. Dukic, S., Iyer, P.M., Mohr, K., Hardiman, O., Lalor, E.C., Nasseroleslami, B.: Estimation of coherence using the median is robust against EEG artefacts. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS. 3949–52 (2017).