Investigating emotional perception in abstract art: The role of colour

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We conducted an experiment in which participants ranked ten abstract paintings based on six emotional descriptors according to the circumplex model of affect, which proposes that affective states derive from two fundamental neurophysiological systems, and that each emotion can be understood as a linear combination of these two systems. The sample consisted of 55 Brazilian participants (mean age = 31; SD = 1.1; 29 women), who met specific inclusion criteria regarding age, education, medical and ophthalmological conditions. To analyse the ranking data, we combined two psychophysical methods, effectively mapping absolute ranking data onto points within a unidimensional continuum. Correlations among the six emotional scales were assessed using Pearson's coefficient, revealing negative correlations for tense-calm, enthusiastic-depressive, and exciting-boring, and a positive correlation for exciting-enthusiastic. We analysed the colour structure of each painting in the CIE Lab colour space, deriving three colorimetric dimensions: ellipse area, axis ratio and hue angle. We conducted a Multiple Linear Regression to investigate statistical relationships between the colorimetric structure of the paintings and the emotional intensity. The regression shows a tendency for saturation (ellipse area) in influencing some emotions. Our results suggest that abstract paintings can be mentally categorised into emotional continua, with these continua displaying a logical interval organisation within opposing emotional dimensions. The lack of a relationship between colorimetric structure and the emotional intensity of the paintings suggests that colour may not significantly influence emotional judgment, while other elements and attributes within visual perception may play a more significant role and require further investigation.

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Introduction

Art serves as a profound medium for expressing human emotions, eliciting both universal and culturally specific emotional responses. These emotional reactions are fundamental to how we engage with and appreciate artworks, deepening our connection to them. While universal emotions can be evoked by elements such as colour, line, and form [1], individual preferences shaped by personal experiences add complexity to the understanding of how emotional responses are elicited by visual stimuli [2].

The psychology of art has gained renewed interest through experimental approaches, driven by computational advances that offer new research perspectives [3-4], facilitating the exploration of statistical regularities in works of art. This has led to intriguing findings, such as the observation that artists often incorporate specific characteristics of natural scenes, which tend to be more aesthetically preferred [5-6]. However, while these studies predominantly focus on quantifying preference, the aesthetic experience, when examined through its diverse historical, cultural, and emotional lenses, remains a complex phenomenon that poses significant challenges [7]. It cannot be reduced to a mere indicator of preference. The appreciation of art evokes a wide range of reactions with varying intensities, and the aesthetic experience emerges from the dynamic interaction between distinct neural processes [8]. Emotions play a fundamental role in the study of aesthetic experience, essential for the full realization of it [9], modulating both bottom-up sensory-driven processes, which are rapid and universal, and top-down processes, which are slower, individual, and context-dependent.

To address this gap, we conducted an experiment using the circumplex model of affect [10] to measure the emotional intensity of paintings. This model proposes that emotions are organised in a circular structure based on two fundamental neurophysiological systems and predicts a linear combination of these systems, resulting in complementary or opposing responses. This model allows mapping emotions into a dimensional continuum and has been successfully applied in quantifying emotional responses to the colour wheel, evoked by different components such as hue, chroma, and lightness [11] This suggests the feasibility of developing universal models of colour emotion and colour harmony, with evidence that this is relatively cultural-independent.

We propose a methodology based on a ranking order procedure, designed to be easily executable outside traditional laboratory settings. This approach accommodates larger and more diverse groups, including children and individuals with varying educational levels [12]. It is particularly advantageous in scenarios with limited initial data and constrained experimental resources, as often encountered in social experiments and preference studies. Using this methodology, we can collect and analyse data on a quantitative scale through psychophysical methods [13], offering a strong database to analyse how emotions are influenced by image features like shapes, brightness, or colour.

We analysed the colour structure of the paintings to verify if their distances on the scales could be justified by similarities or differences in the use of colour. We derived three statistical parameters: saturation, hue angle, and colour balance between the blue-yellow and red-green axis [14]. By examining these metrics, we aim to understand how specific colour patterns and arrangements contribute to the emotional experiences of the viewers, thereby linking objective visual properties to subjective emotional responses. Such studies can help unfold peculiarities, differences and similarities, providing deeper insights into how cultural and geographic factors influence emotional preferences [15-16].

Methods

Participants

The sample included 55 participants (mean age = 31; SD = 1.1; 29 women) between 18-68 years, with completed high school, no visual arts degrees, no more than 2 years working in art/design. All had corrected visual acuity of 20/20 or better (ETDRS–Tumbling E chart, Xenônio Rep. Prod., São Paulo, Brazil), and were free from conditions that affect vision. Colour blindness was checked using the 38-plate Ishihara test (Kanehara Trade Inc., Tokyo, Japan).

All participants volunteered to take part in the study without receiving any financial compensation. The Ethics Committee for Human Research at the Institute of Psychology, University of São Paulo, Brazil. granted ethical approval for this study (31528620.8.0000.5561). We obtained informed consent from all participants, and the study followed the ethical principles outlined by the American Psychological Association.

Stimuli

We used ten printed images of paintings as stimuli (Figure 1) devoid of figurative and realistic elements, by European artists from the mid-19th to early 20th century, published with free access on the Internet. The paintings were printed on matte photographic paper A4 210g/m², respecting appropriate proportions and cuts, and laminated for durability during the study.

We used six emotional descriptors: tense, calm, enthusiastic, depressive, exciting, and boring (Figure 2), chosen according to the circumplex model of affect [10]. This model suggests emotions form a circular structure based on two fundamental neurophysiological systems, where each emotion is a linear combination of these systems, predicting complementary or opposing responses.

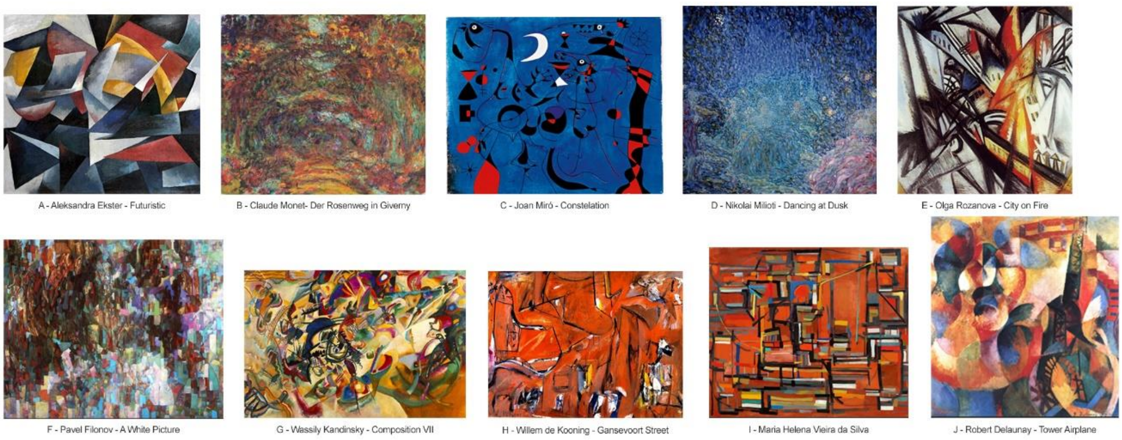

Figure 1: Ten printed images of paintings used as stimuli, devoid of figurative and realistic elements, by European artists from the mid-19th to early 20th century. All images are published with free access on the Internet.

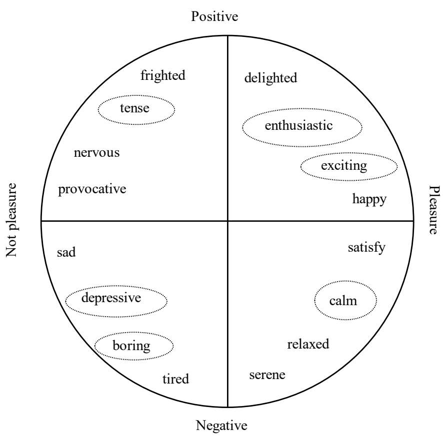

Figure 2. Adaptation of the circumplex model of affect. We used six emotional descriptors for the study: tense, calm, enthusiastic, depressive, exciting, and boring. This model suggests emotions form a circular structure based on two fundamental neurophysiological systems, where each emotion is a linear combination of these systems, predicting complementary or opposing responses.

Procedure

After completing the demographic questionnaire and ophthalmological tests, participants who met the criteria were directed to a room illuminated by three 6500k fluorescent lamps with CRI > 90, using a diffuser to eliminate shadows and maintaining an average luminance of 45 cd/m^2 measured by an Everfine SPIC-200 spectrometer. The researcher, positioned on the other side of the table, provided the instructions as follows: "An emotional descriptor will be randomly selected, which I will read and place on the table. You should rank the ten images of paintings according to the intensity of this descriptor. There will be six descriptors in total. If you do not know the meaning of any descriptor, please let me know. You may withdraw from the experiment at any time."

After finishing the ranking for the first emotional descriptor, the researcher recorded the order in a spreadsheet, collected all the images, shuffled them, and placed them back on the table face down. The procedure was repeated for all descriptors. If any participant did not know the meaning of it, they were to inform the researcher. The procedure would be to skip this ranking and move on to the next descriptor until the end of the experiment. However, this participant would be removed from the sample.

The entire experiment, including demographic questionnaire and ophthalmological tests, took around forty minutes to be completed.

Psychophysical scale

We constructed a quantitative interval scale for each emotional descriptor by combining two methods derived from psychophysics known as the Law of Comparative Judgment [17-18]. These methods allow the absolute ranking data to be mapped into points within a unidimensional continuum [19], facilitating a more comprehensive and robust statistical analysis.

For that, we organised the ranking data into a binary correlation matrix, containing the probabilities of each painting being chosen over another [18]. Using this matrix, we applied case 5 of the judgment equation [17], assuming normally distributed variance and equal variance for all stimuli. We converted the probability values from the matrix into distances, adapting a normal bell curve where 1 unit represents 75%, the midpoint between a random guess and absolute certainty [20]. The painting with the lowest value was defined as zero on the scale, and values for other paintings were added sequentially to position them on the scale.

As this type of scale only allows an estimation of the actual data, assuming a standard error that is similar for all scale positions, we computed an internal consistency using the scale values to create a comparison matrix identical to that obtained experimentally. We calculated the average difference between the two matrices to represent the discrepancy of the scale relative to the data obtained experimentally [21].

Details on the construction of the scale can be found in the Supplementary Material.

Colorimetric structure

We analysed the colour structure of the paintings to verify if the emotional distances between paintings on the scales could be justified by similarities or differences in the use of colour. For this, we adjusted the colour gamut in CIELAB of each painting similar to [14] to derive three statistical parameters: area, which serves as a descriptor for saturation; orientation, providing the inclination of the colour gamut within the plane; and semi-axis ratio, facilitating the assessment of the diversity in the use of colour between red-green and yellow-blue axis (Figure 3).

Since we lack information about the conditions under which the images of the paintings were captured, processed, and transmitted, we did not perform any correction. Our aim is not to conduct an exhaustive colorimetric characterisation but rather to carry out a global comparative study of the chromatic gamut in the paintings. We believe this approach will adequately meet the demands of our work.

The colour metrics of the ten paintings are provided in the Supplementary Material.

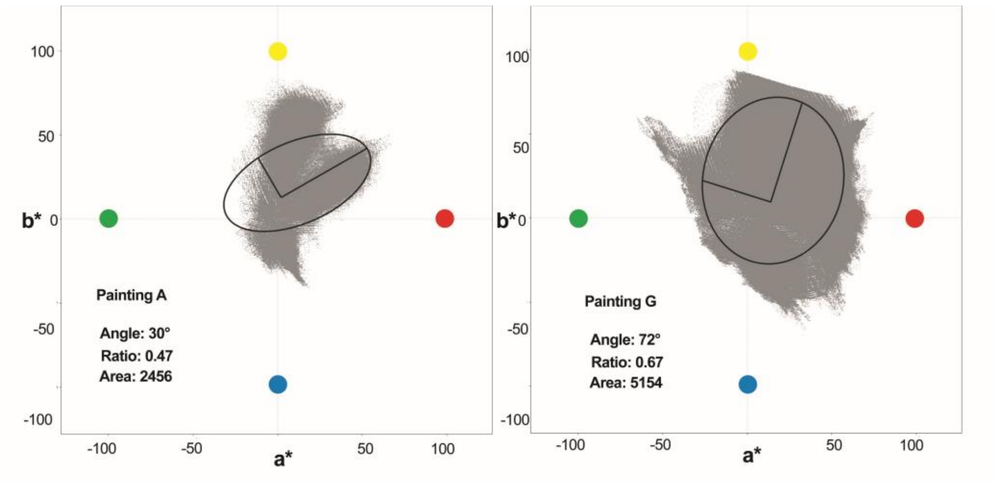

Figure 3: Example of the characterisation of the colour gamut of paintings A (left) and G (right) in the CIELAB. The angle indicates that painting A has a more reddish hue, while painting G tends to a more yellow hue. The ratio between the axis of painting A is smaller than painting G, showing less diversity in the use of colour. The area of the painting A is two times smaller than painting G, indicating the use of a lesser saturated colour.

Results

We plot the results in an interval scale for each emotional descriptor (Figure 4). To determine if there is a statistically significant difference between the paintings on the scale, we apply a paired Student's t-test with a 95% confidence interval, using the scale discrepancy as deviation.

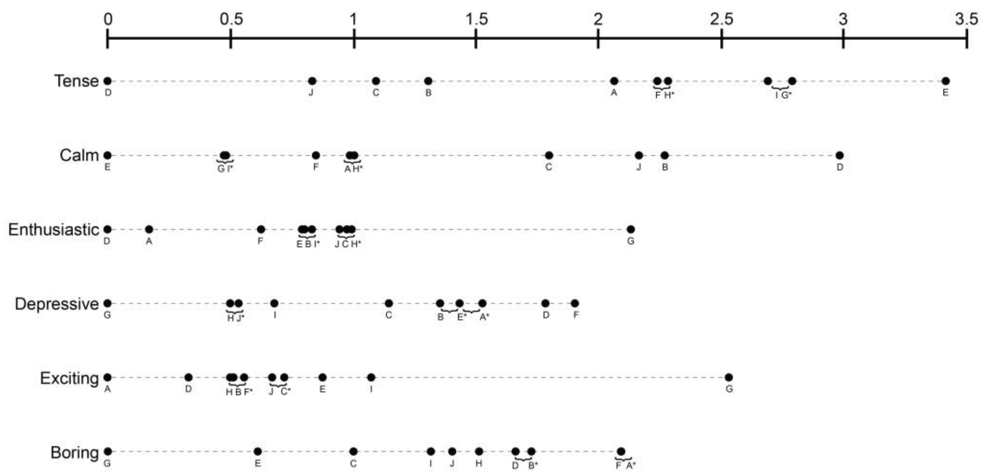

Figure 4: Psychophysical interval scale of the ten abstract paintings for six emotional descriptors constructed using the Law of Comparative Judgment. "" indicate paintings that clustered on the scale, according to Student's t-tests with a 95% confidence interval, using the scale discrepancy as deviation.*

To verify if the circumplex model of affect correctly predicts opposing emotions for the paintings, we conducted Pearson correlation analysis (Table 1). The coefficient revealed negative correlations among tense-calm, enthusiastic-depressive, and exciting-boring ($p < 0.05$), suggesting a direct opposition of these emotional states. A positive correlation was found for exciting-enthusiastic ($p < 0.05$).

	Calm	Enthusiastic	Depressive	Exciting	Boring
Tense	-0.98*	0.44	-0.27	0.44	-0.40
Calm	---	-0.41	0.27	-0.43	0.40
Enthusiastic	---	---	-0.82*	0.90*	-0.79
Depressive	---	---	---	-0.70	0.63
Exciting	---	---	---	---	-0.86*

*Table 1: Pearson's coefficient revealed negative correlations among tense-calm, enthusiastic-depressive, and exciting-boring (*p < 0.05), suggesting a direct opposition of these emotional states. A positive correlation was found for exciting-enthusiastic (*p < 0.05).*

Finally, we conducted a Multiple Linear Regression (Table 2) to explore relationships between emotional intensity and the colour structure of the paintings. Since angles are cyclical (0° = 360°), we transformed the circular variable into sine and cosine components. The sine component better represents values around 90° or 270° (vertical), which corresponds more closely to the variable associated with the blue-yellow axis of colour. Conversely, the cosine component better represents values around 0° or 180° (horizontal), aligning more closely with the variable associated with the red-green colour axis.

Tense

	R^2	p-value
Ratio	0.00	0.90
Area	0.09	0.40
Sin angle*	0.39	>0.05*
Cos angle	0.22	0.17

Calm

	R^2	p-value
Ratio	0.02	0.68
Area	0.11	0.35
Sin angle	0.29	0.10
Cos angle	0.23	0.15

Enthusiastic

	R^2	p-value
Ratio	0.02	0.13
Area*	0.36	0.06*
Sin angle	0.18	0.22
Cos angle	0.017	0.72

Depressive

	R^2	p-value
Ratio	0.10	0.36
Area*	0.65	<0.05*
Sin angle	0.09	0.39
Cos angle	0.01	0.70

Exciting

	R^2	p-value
Ratio	0.03	0.60
Area	0.22	0.17
Sin angle	0.07	0.44
Cos angle	0.06	0.50

Boring

	R^2	p-value
Ratio	0.00	0.90
Area	0.14	0.28
Sin angle	0.00	0.8
Cos angle	0.11	0.33

Table 2: Multiple Linear Regression between emotional intensity and colour structure of the paintings. For tense, the sin angle variable is almost significantly associated ($p = 0.051$). For depressive, the model explains a large portion of the variability between the area ($R^2 = 0.665$). The model explains a moderate amount of variability ($R^2 = 0.360$) of the area for enthusiastic, but the relationship is not statistically significant at the 95% level (p-value = 0.067).

For tense, although the p-value is slightly greater than 0.05 (p-value = 0.051), it is very close, suggesting that the sin angle variable is almost significantly associated with tenseness. The Durbin-Watson value suggests that the residuals are well-behaved, with no significant autocorrelation.

For depressive, the model explains a large portion of the variability ($R^2 = 0.665$), indicating that the area significantly affects the perception of depression in the paintings. The negative coefficient of area suggests that larger areas are associated with lower depressive scores, and this relationship is highly significant (p-value = 0.004). There is no evidence of autocorrelation issues, and the overall fit of the model appears reliable. Area also seems to have a positive influence on the perception of enthusiasm in the paintings, but the relationship is not statistically significant at the 95% level (p-value = 0.067). The model explains a moderate amount of variability ($R^2 = 0.360$), but potential issues with the normality of residuals (Omnibus test) should be considered.

Given the small sample size of painting (n = 10), caution is advised when generalising these results.

Discussion

Almost all paintings were easily classified under the descriptors tense, calm, boring, and depressive, suggesting a consistent interpretation of these emotional descriptors for classifying the selected paintings. For exciting and enthusiastic, the situation proved to be more complex. Painting G showed almost twice the distance compared to the others, which are very close on the scale. (this painting seems to pop-up) This prominence seems to reflect the influence of the aesthetics of perception [9], where the visual elements of the painting evoke universal emotions. On the other hand, the lesser distinction among all other paintings under these descriptors highlights the influence of cognitive aesthetics [7-8] where individual interpretation and contextualisation play a more prominent role in the perception of these emotional states.

The results further underscore the relationships between different emotional descriptors, as revealed by the Pearson correlation coefficient. For pairs of opposite descriptors such as tense-calm, depressive-exciting, and enthusiastic-boring, the correlations were negative, indicating a clear opposition between these emotional states. This suggests that these emotions are experienced in mutually exclusive ways, consistent with the structure of the circumplex model of affect [10]. This model, which organises emotions along two primary dimensions; valence (pleasure-displeasure) and arousal (activation-deactivation), appears well-suited for quantitative analyses of emotional perception in complex visual stimuli. Its capacity to map emotional responses onto a circular continuum aligns with our findings, supporting its applicability in studying how visual elements, such as colour, evoke distinct emotional experiences [11].

While colour saturation seems to impact the perception of certain emotions in paintings, in cases as enthusiastic and depressive, colour is not the only determining factor, suggesting that other visual elements play a more significant role in shaping emotional responses. Although the regressions did not reveal a strong trend in the colorimetric parameters of the paintings for emotional judgment, these results should not be generalised. One of the key limitations is the small sample size of stimuli, with only ten paintings, which significantly constrains the linear regression analysis and limits the ability to detect more subtle relationships between too many variables. The selection of paintings may have introduced biases. We did not choose the paintings based on colorimetric criteria, conducting the analysis retrospectively. The similarity in artistic styles and the period in which the paintings were created may have also constrained and biassed the analysis. Moreover, the selection of emotional descriptors was arbitrary, using only direct adjectives instead of considering indirect synonyms. The field of art aesthetics is vast, encompassing numerous factors beyond colour that affect emotional perception.

Acknowledging these limitations, a key characteristic of the proposed methodology is its simplicity, quick execution, and robust psychophysical analysis, allowing measures of high internal consistency and applicability across different ages or educational levels. This analysis method is a step forward in studying emotions, as it measures statistical distances rather than relying on classification or categorisation, which typically use categorical or ordinal scales and provide less information [22]. The ranking procedure measures dimensional salience, indicating that more evident or priority stimuli are externalised first compared to stimuli of lower subjective value. It is one of the best methods for measuring preference or high degrees of subjectivity [23]. By measuring points on the scale at intervals using standard deviation units of the sample, results from studies with different experimental procedures can be combined on the same scale [24], which is crucial when studying complex subjective events that require different levels of analysis.

Future studies involving a larger, more diverse set of paintings and a broader range of emotional descriptors could provide deeper insights into how colour shapes emotional perception in art. Additionally, exploring other visual and contextual attributes may offer a more comprehensive understanding of how individuals perceive and interpret emotions through artistic works.

Conclusions

We propose a practical methodology, designed to be easily executed outside traditional laboratory settings, particularly beneficial in situations with limited initial data and constrained experimental resources, as often encountered in social experiments and preference studies, but with real quantitative power of analysis. Our results suggest that abstract paintings can be mentally categorised along emotional continua, with these continua displaying a logical interval organisation within opposing emotional dimensions. The circumplex model of affect appears particularly well-suited for quantitative studies of emotional perception in complex visual stimuli.

The lack of a strong relationship between the colorimetric structure and the emotional intensity of the paintings suggests that colour may not significantly influence emotional judgment in paintings, and other elements and attributes within visual perception may play a more prominent role and warrant further investigation.

Our results suggest that this experiment could be effectively conducted on an online platform, under less controlled conditions. This would allow for the evaluation of a larger number of paintings and emotional descriptors, helping on the development of a computational model that predicts emotional intensity based on various image features, deepening our understanding of the aesthetic experience.

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