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Affective Effects of Fractal Dimension and Color Attributes on Preference for Chromatic Exact Fractals

Shigen Fang Ogata[1)] (Member) **Yiyang Bi**[2)] (Non-Member)

Tatsunori Matsui[3)] (Non-Member)

1) Graduate School of Education, Hyogo University of Teacher Education

2) School of Human Sciences, Waseda University

3) Faculty of Human Sciences, Waseda University

sogata@hyogo-u.ac.jp

Abstract

This study investigates the impacts of fractal dimension and color attributes on preference for chromatic exact fractals through two experiments. Experiment 1 established the semantic differential scales suitable for affective evaluations of colored exact fractals. Experiment 2 collected affective evaluations for colored exact fractals from which four factors were extracted, including the Preference factor. Data analysis replicated the ascending trend between preference and fractal dimension level reported by previous studies. Regarding the color attributes, we detected an evident dislike for exact fractals in dark colors and a weak dislike for those in saturated colors. Further, exact fractals of warm hues were more preferred than those of cool hues on most tones.

1. Introduction

Fractals, in the realm of visual objects, are intricate geometric shapes that exhibit self-similarity across different scales. This means that if we magnify a fractal several times, we can discern a structural pattern repeating at every level of magnification. Fractal patterns can be found extensively in nature as well as in mathematical constructions. An important concept related to fractals is the fractal dimension. The fractal dimension represents the rate at which the detail of the fractal, namely the number of segments, increases as the scale at which the fractal is measured becomes smaller. Fractals can be classified into two types: statistical fractals and exact fractals. A statistical fractal is characterized by some statistical properties recurring across scales, meaning that structures on different scales are not precisely the same. In contrast, an exact fractal is generated by a deterministic algorithm that repeats a structure exactly across scales.

The first style of exact fractal was the Cantor set, introduced by Georg Cantor in 1883 [1]. A Cantor set is composed of line segments that have a fractal dimension between zero and one. Then, in 1904, Helge von Koch proposed the Koch curve, which is the first style of exact fractal that possesses fractal dimensions between one and two [1]. A dimension between one and two means that the fractal is a plane shape, but its segments cannot cover the entire region enclosed by this shape on the plane. Later, Waclaw Sierpinski published two styles: the Sierpinski Triangle and the Sierpinski Carpet [2]. More styles were created after that, leading Benoit B. Mandelbrot to establish the field of fractal geometry in 1975 [3]. Mandelbrot also created the Mandelbrot set, which is a style of exact fractal that is not only complicated in composition but also aesthetically intriguing [1,4].

Although mathematical research on exact fractals has existed for one and a half centuries, research on the psychological effects of the perception of exact fractals started very recently. Hagerhall et al. [5] pioneered this line of research. They studied how viewing exact fractals affected human alpha brainwave activity using quantitative EEG. A year later, Bies et al. [6] conducted the first behavioral study on human preference evaluation for exact fractals. Bies et al. used four styles of fractals differing in symmetry and recursion method as stimuli, which were Exact Midpoint Displacement, Sierpinski Carpet, Symmetric Dragon, Golden Dragon, and Koch Snowflake. They found a significant positive linear trend between fractal dimension value and preference for every style, despite some styles also showing significant higher-order relations. These results suggested that a generally ascending trend exists across styles of exact fractals. Then, Robles et al.'s experiment in 2020 [7] recruited both adults and children, aiming to clarify whether preference for fractals differs across age groups. The exact fractals used in their experiments were Exact Midpoint Displacement fractals and H-Tree fractals. Results revealed higher preference assessment for exact fractals of higher dimension values for both age groups, implying the robustness of the trend reported earlier by Bies et al. [6]. Further, Robles et al.'s experiment in 2021 [8] investigated the aesthetic evaluation of "global forest" patterns, which were fractal designs in human-made interior spaces. These patterns included an exact fractal style named "tree-seed" patterns. Regarding this style, the results of this experiment showed a linear trend in which preference increased with fractal dimension value. To summarize, all three previous studies on preference for exact fractals detected an ascending tendency between preference and fractal dimension.

However, as these studies all used achromatic fractals as stimuli, no knowledge has been obtained about the effects of fractal dimension on preference for chromatic exact fractals, that is, exact fractals in chromatic colors. Another vital but untouched question is how color attributes influence preference for chromatic exact fractals. As chromatic exact fractals are widely used in digital art and design [9-11], exploration of these questions will deepen our understanding of how fractal arts affect viewers' affective states. For these reasons, this study intends to empirically investigate how fractal dimension and color attributes influence preference for chromatic exact fractals.

This study conducted two psychological experiments. Section 2 introduces the designs of the exact fractal images used as stimuli. Section 3 describes Experiment 1, which constructed semantic differential (SD) scales for affective evaluations of exact fractals. Section 4 describes Experiment 2, which elicited affective evaluations for the fractals. Section 5 describes a factor analysis that extracted the main factors underlying the affective evaluations, one being the preference assessment. Section 6 describes the data analysis on how fractal dimension and color properties affected the preference assessment. Section 7 discusses the results of the data analysis by comparing them with the results of previous studies [Note 1].

2. Fractal Patterns Used in Experiments

The stimuli used in the experiments consisted of 306 digital images, resulting in a sample size of $n = 306$. This sample size is sufficiently large, as it meets both the criteria for the absolute number of samples (n) and the sample-to-variable (n/v) ratio required for behavioral studies employing exploratory factor analysis. Specifically, according to Comfrey and Lee's guidelines [12], our sample size qualifies as Good since it exceeds the threshold of $n > 300$. Regarding the n/v ratio, this is calculated as the number of samples divided by the number of rating variables, which in this study corresponds to the SD scales. Watson [13] reported that $n/v > 5.0$ is a well-accepted criterion based on a survey of the multivariate statistics literature, while Nunnally [14] and Everitt [15] recommend a stricter criterion of $n/v > 10.0$. The n/v ratio of our sample is 17, surpassing both of these benchmarks.

Each digital image contains a different exact fractal at its center. We generated the images using *Turtle* [16] and *Pygame* [17], two Python-based graph plotting packages. Every image has a size of 1968 (width) × 1682 (height) pixels. The background color of the images was medium grey ($R = 128$, $G = 128$, $B = 128$). The fractal patterns varied in four attributes: fractal style, fractal dimension, and two color attributes, which were hue and tone.

This study employed three styles of exact fractals: Sierpinski Carpet, Golden Dragon, and Koch Curve. Each style contains 102 fractals. As the former two styles have been used by Bies et al. [6] and Robles et al. [7], using the two styles could help compare our results with the previous studies' results. Koch Curve has not been investigated in previous studies, so it can help us assess the robustness of the psychological effects previously reported.

With regard to fractal dimension, the fractals were categorized into three levels: one-third had a dimension value of 1.1, labeled as *low-dimensional*; another one-third had a dimension value of 1.5, labeled as *intermediate-dimensional*; and the remaining one-third had a dimension value of 1.9, labeled as *high-dimensional*. The fractal dimension was defined using the box-counting dimension, as in Robles et al.'s study [8].

Fractal images at these dimension levels were generated using recursive algorithms implemented in Python. To create Golden Dragon fractals, the algorithm at each iteration divided a line segment into two sub-segments, r_1 and r_2, whose lengths are scaled by the golden ratio ϕ as defined in Equations (1) and (2):

$$r_1 = (1/\phi)^{1/\phi} \tag{1}$$

$$r_2 = r_1^2 \tag{2}$$

Then, we adjusted two angles θ_1 and θ_2, which determined how the two sub-segments were joined to each other, and the number of iterations (i.e., recursive depth) to manipulate the fractal dimension. The angles θ_1 and θ_2 respectively represent the degrees to which r_1 and r_2 deviate from the original line orientation.

Regarding the algorithm generating Sierpinski Carpet fractals, at each iteration, it divided a square grid into nine smaller squares, arranged in a 3×3 layout, and removed the central square. The recursion was applied to the remaining squares, repeating the process for a specified number of iterations (i.e., recursive depth). To vary the fractal dimension, we adjusted the recursive depth and modified the patterns of grid removal by selectively retaining or removing squares within the 3×3 subdivided grids at each iteration.

Our algorithm for generating Koch Curve fractals was based on code provided by the website GeeksforGeeks [18]. We modified the values of the segment length, the recursive depth, and the scaling factor (the proportion by which each segment was reduced in size) at each iteration of the recursive function in this algorithm to manipulate the fractal dimension.

Within these algorithms, the values of the variables controlling the fractal dimension were determined through trial and error. During this process, the dimension values of the generated fractals were computed and checked using the package *Fractal: A General Purpose Architecture for Estimating the Fractal Dimension of Any Pattern or Geometry* [19]. Figure 1 shows the nine fractals of the color *black* as a demonstration of how the stimuli vary along fractal style and fractal dimension.

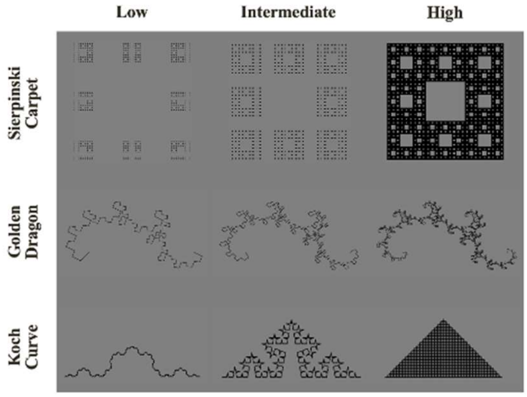

Figure 1. The *black* fractals used in this study arranged according to fractal style (rows) and dimension (columns).

The colors of the fractals included 32 chromatic colors. Additionally, although this study aimed to clarify the effects of chromatic colors, we also used *black* and *white*, which were achromatic colors, to provide participants with a more complete impression of how the fractals appeared in different colors. The 32 chromatic colors, listed in Table 1, were a Munsell color palette that the Berkeley Color Project (BCP) developed for experimental research on color preferences [20,21]. The hues included four primary hues: *red*, *green*, *blue* and *yellow*, and four secondary hues: *orange*, *purple*, *cyan* and *chartreuse*. The lightness and chroma were incorporated into a single attribute termed "tone" in this study. Tone has four levels. The *saturated* level contained the most saturated colors that the BCP chose for this palette. The *light* level consisted of the colors situated halfway between the saturated colors and the colors of value = 9 and chroma = 1 on the hues. The *muted* level is composed of the colors located halfway between the saturated colors and the colors with value = 5 and chroma = 1 on the hues. The *dark* level included the colors located halfway between the saturated colors and the colors of value = 1 and chroma = 1 on the hues. The colors on each hue have the same chroma value. The BCP used the Munsell glossy series when selecting colors for this palette and then transformed the Munsell coordinates of the colors into CIE xyY values using Wyszecki and Stiles's renotation table [20]. Figure 2 illustrates the appearance of different tones using *blue* fractals as examples at each dimension level. Figure 3 presents the appearance of the eight chromatic hues, as well as *black* and *white*, using *saturated* fractals as examples at each dimension level.

3. Experiment 1: Adjective Collection

3.1 Objective

Experiment 1 aimed to collect adjectives that can depict affective impressions of exact fractals. Through selecting the most representative ones from the collected adjectives and combining them with rating scales proposed in previous studies, we developed a list of SD scales suitable for affective evaluations of exact fractals. This experiment design referred to Fukuda and Fukuda's experimental paradigm on constructing SD scales of affective evaluations [22].

Table 1. The 32 chromatic colors that the palette of the Berkeley Color Project [12] uses.

Hue level	Tone level	Munsell coordinates		
		Hue	Value	Chroma
red	saturated	5 R	5	15
red	light	5 R	7	8
red	muted	5 R	5	8
red	dark	5 R	3	8
orange	saturated	5 YR	7	13
orange	light	5 YR	8	6
orange	muted	5 YR	6	6
orange	dark	5 YR	3.5	6
yellow	saturated	5 Y	9	12
yellow	light	5 Y	9	6.5
yellow	muted	5 Y	7	6.5
yellow	dark	5 Y	5	6.5
chartreuse	saturated	5 GY	8	11
chartreuse	light	5 GY	8.5	6
chartreuse	muted	5 GY	6.5	6
chartreuse	dark	5 GY	4.5	6
green	saturated	3.75 G	6.5	11.5
green	light	3.75 G	7.75	6.25
green	muted	3.75 G	6	6.25
green	dark	3.75 G	3.75	6.25
cyan	saturated	5 BG	7	9
cyan	light	5 BG	8	5
cyan	muted	5 BG	6	5
cyan	dark	5 BG	4	5
blue	saturated	10 B	6	10
blue	light	10 B	7.5	5.5
blue	muted	10 B	5.5	5.5
blue	dark	10 B	3.5	5.5
purple	saturated	5 P	4.5	17
purple	light	5 P	7	9
purple	muted	5 P	5	9
purple	dark	5 P	3	9

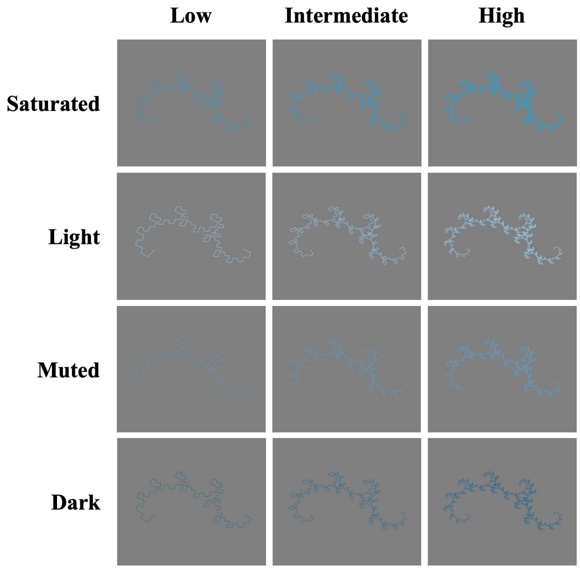

Figure 2. Twelve *blue* Golden Dragon fractals as examples of different tones at each dimension level.

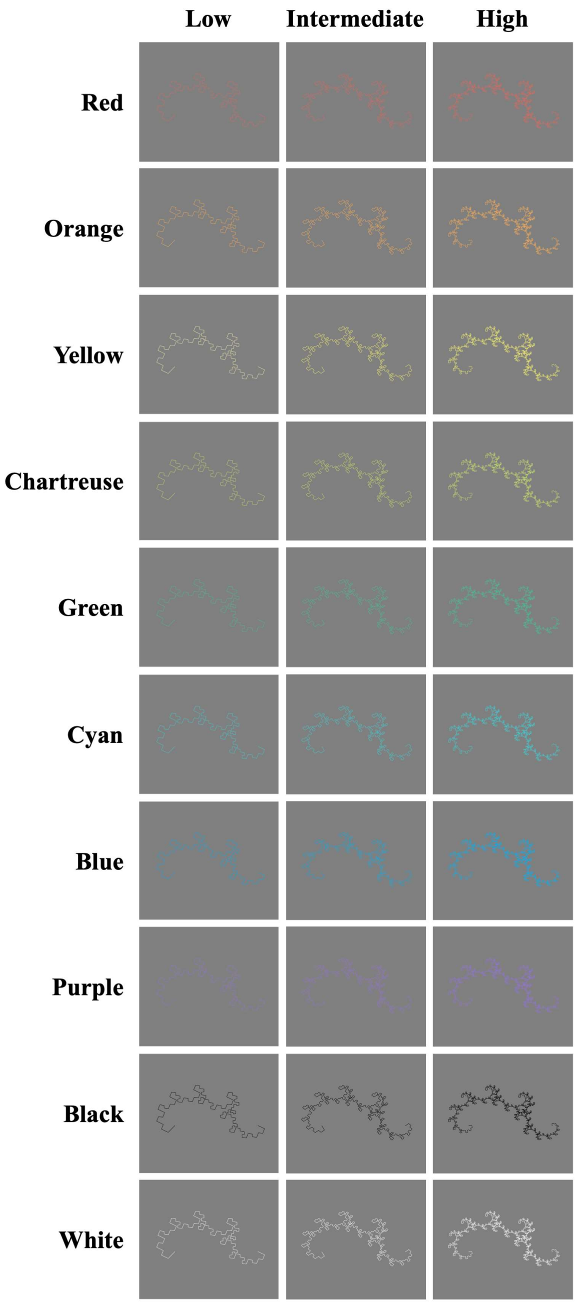

Figure 3. Thirty *saturated* Golden Dragon fractals as examples of different hues at each dimension level.

3.2 Participants and stimuli

This experiment had 12 participants who were students at Waseda University with ages ranging from 21 to 24 (M = 21.8 years, SD = 1.0). All participants reported not having deficiencies in color vision and not having professional experience in the fields of visual arts or design. We obtained informed consent for participation from all participants.

The experiments in this study conformed to the ethical guidelines concerning research with human subjects of the Waseda University Office of Research Ethics. The experiments used the Japanese language, so we only recruited native Japanese speakers.

This experiment used all 306 fractal images as stimuli, each with a size of 1968 (width) × 1682 (height) pixels. The perception of the fractal dimensions in exact fractal images is insensitive to viewing distance (or viewing angle) due to their self-similarity. This property, as described in Section 1, ensures that the structural pattern of visual details of an exact fractal remains consistent regardless of the scale at which the fractal is viewed. Thus, in this study, participants were free to follow their natural viewing habits.

3.3 Procedure

Due to the Covid-19 pandemic during that period, we performed the experiment by arranging an online meeting for each participant using Zoom (https://zoom.us).

During a meeting, we first described the objective and procedure of the experiment. Then, we sent the link of a Google Drive folder in which the fractal images were stored to the participant. The participant downloaded and opened the images on their own PC. We asked the participant to view the fractals and provide as many adjectives as possible that they thought could describe their impressions of these fractals. We emphasized that every adjective should be able to describe a considerable proportion of the fractals. The participant entered the adjectives in a Microsoft Excel sheet that we sent to them. During the participant's answering, the participant was allowed to switch freely between the answer sheet and the images. No time limitation was imposed on the answering.

3.4 Results

This experiment collected a total of 246 adjectives (number of adjectives per person: M = 20.5, SD = 1.5), encompassing 108 unique adjectives. Adjectives that differed only in the kanji or kana spelling were counted as the same adjective.

We selected the most representative adjectives by the following five steps:

(1) We grouped the 108 adjectives by classifying the adjectives that had similar semantic meanings into one group.

(2) We counted the number of occurrences for each adjective.

(3) For each group, we summed up the numbers of occurrence across the adjectives included and took this sum as the number of occurrences for this group.

(4) Considering that the adjectives selected should not be too many to cause participants' fatigue when used in an SD rating experiment, we selected the adjective groups whose numbers of occurrences were no less than four. In this manner, 15 groups were selected.

(5) Within each selected group, we selected the adjective that best represented the group (e.g., the adjective that had the largest number of occurrences within the group).

Fifteen adjectives were selected using this procedure. We then determined the antonym for each of them by referring to Japanese

Table 2. Japanese version and English translation of the 15 pairs of adjective antonyms developed via Experiment 1.

Japanese version	English translation
寒い － 暖かい	cold - warm
複雑な － シンプルな	complex - simple
尖っている － 丸みのある	sharp - blunt
やわらかい － かたい	soft - hard
上品な － 下品な	graceful - awkward
小さい － 大きい	small - large
美しい － 醜い	beautiful - ugly
明るい － 暗い	bright - dark
気持ちが良い － 気持ちが良くない	cheerful - gloomy
可愛い － 可愛くない	lovely - not lovely
細かい － 粗い	fine - rough
薄い － 濃い	plain - strong
綺麗な － 汚い	clean - dirty
細い － 太い	thin - thick
重たい － 軽い	heavy - light

dictionaries. Table 2 lists the Japanese version and English translation of the 15 SD scales.

In addition, Okajima et al.'s psychological studies [23,24], which used vertical stripe patterns including fractal stripe patterns as stimuli, reported that fractal attributes influenced Japanese participants' evaluations of those patterns on two scales: Artificial - Natural (人工的な － 自然な) and Pleasant - Unpleasant (快い － 不快な). Also, Cho and Haraguchi [25] and Cho, Haraguchi and Miura [26] found that the fractal dimension of a painting was capable of affecting the hedonic feeling elicited by the painting. In consideration of these results, our study added Artificial - Natural and Pleasant - Unpleasant, as well as Positive - Negative (ポジティブな － ネガティブな), which evaluates the hedonic valence, into the list of SD scales developed via our experiment. As a result, we obtained a list of 18 SD scales.

4. Experiment 2: Affective Evaluation

4.1 Objective

Experiment 2 used the SD scales developed in Experiment 1 to elicit people's affective evaluations of exact fractals. We extracted the main factors underlying the evaluations through a factor analysis of the rating data.

4.2 Participants, stimuli and procedure

In Experiment 2, we recruited 19 participants via CrowdWorks (https://crowdworks.jp), an online crowdsourcing platform. All participants were native Japanese speakers. They reported not having deficiencies in color vision and not having professional experience in the fields of visual arts or design. No one had participated in Experiment 1. We obtained informed consent for participation from all participants.

We built the experiment program using the online survey tool Qualtrics (https://www.qualtrics.com/jp/) and sent the link to participants via short messages on CrowdWorks. Participants were required to use PCs to complete the program. The stimuli were the same 306 fractal images used in Experiment 1.

The program presented these images one at a time in a random order; that is, this experiment had 306 trials. In each trial, participants were required to rate their affective impressions of the fractal being displayed using the 18 SD scales developed in Experiment 1. A list of the scales, which were seven-point Likert scales, was placed below the stimulus image. The order of scales in this list was randomly determined. Participants were free to scroll back to observe the image during their answering. No time limitation was imposed on the answering. When participants finished a trial, they clicked a button at the bottom of the webpage to enter the next trial.

Data screening after the experiment noted that three participants provided careless answers, e.g., repeating the same rating to successive scales, so their data were excluded from data analysis. The remaining 16 participants' ages ranged from 26 to 54 (M = 36.4 years, SD = 7.4). Kato's [27]; Tsutsui and Ohmi's [28]; and Fang, Muramatsu, and Matsui's [29] experiments all employed SD rating scales to assess Japanese participants' affective evaluations of colored visual patterns. These studies had 13, 9, and 12 valid participants, respectively, and obtained reliable ratings. Similarly, Ou et al.'s [30] SD-method experiment had 14 British and 17 Chinese participants and collected reliable ratings of color emotions for both cultural groups. Moreover, Bies et al.'s Experiment 2 [6] divided participants into two subgroups, which had 12 and 6 participants respectively, and found an ascending trend between fractal dimension and preference in both subgroups. These studies indicate that our data analysis had a reasonable number of participants (which is 16, as noted above) to investigate whether similar ascending trends could also be observed for colored fractal patterns.

5. Factor Analysis of Affective Evaluations and Computation of Preference Score

We investigated the psychological dimensions underlying the affective evaluations of the exact fractals by performing an exploratory factor analysis on the SD rating data collected in Experiment 2. The Cronbach's α coefficients of the SD scales averaged 0.73 (SD = 0.08, all above 0.60). This indicates that these scales had moderate to high degrees of inter-rater reliability, according to Robinson, Shaver and Wrightsman's criterion for exploratory research [31]. Thus, we averaged the rating data across participants for each SD scale and conducted the factor analysis on the averaged data.

Regarding the method for determining factors, Cho and Haraguchi [32] reviewed the SD scales used in previous studies about Japanese people's affective evaluations of paintings and used the ordinary least squares method to investigate the factorial structures of SD scales that they developed based on this review. In reference to their work, we also used the ordinary least squares method. We defined the main factors as those with eigenvalues greater than 1.0.

Table 3. Factor loadings and grouping of the SD scales after the promax rotation.

Factor identity	SD scale	Factor loading			
		Factor 1	Factor 2	Factor 3	Factor 4
Factor 1 (Preference)	cheerful - gloomy	**0.95**	0.05	0.07	-0.05
	pleasant- unpleasant	**0.92**	0.01	0.03	0.04
	lovely- not lovely	**0.91**	0.02	-0.10	-0.02
	positive - negative	**0.89**	-0.09	-0.14	-0.18
	bright - dark	**0.87**	0.04	-0.07	-0.27
	clean - dirty	**0.86**	0.00	0.13	0.24
	beautiful - ugly	**0.85**	-0.01	0.15	0.25
	graceful - awkward	**0.75**	0.07	0.09	0.26
Factor 2 (Weightiness)	heavy- light	-0.20	**-0.98**	0.15	0.24
	plain - strong	0.00	**0.82**	0.02	-0.18
	small- large	-0.12	**0.72**	-0.08	0.23
	thin - thick	-0.02	**0.70**	0.02	0.30
Factor 3 (Toughness)	soft- hard	0.08	0.27	**-0.83**	0.17
	artificial - natural	0.07	0.05	**0.80**	-0.37
	sharp - blunt	0.27	-0.13	**0.74**	0.03
	cold - warm	-0.18	0.14	**0.37**	0.14
Factor 4 (Complexity)	complex – simple	-0.05	-0.15	-0.22	**0.85**
	fine - rough	0.28	0.07	-0.02	**0.78**
Variance explained		36%	16%	12%	11%

Then, we rotated the factors using the promax method. The rotation led to four main factors as shown in Table 3. Table 3 also shows the post-rotation factor loadings for each SD scale.

We interpreted each main factor based on its factorial structure, that is, the SD scales having large loadings on that factor. As Factor 1 represented how cheerful, pleasant, positive, and beautiful the fractals were evaluated to be, we inferred that this factor showed the degree to which a person liked a fractal pattern. Thus, we named the factor "Preference". Factor 2 included the heaviness evaluation along with the senses of density, largeness, and thickness, which were usually associated with weighty objects. Thus, we named it "Weightiness". Factor 3 represented how hard, artificial, pointed, and cold the stimuli appeared, so we named it "Toughness". Factor 4 assessed how complex and rough the stimuli looked; therefore, we named it "Complexity". The factors Weightiness and Complexity showed a medium-level positive correlation (r = .54), while the other correlations were all below 0.20. The factors explained a total of 75% of the overall variance within the SD ratings, implying that these factors were sufficient to explain the information contained in the affective evaluation data.

Adopting Fang, Muramatsu and Matsui's methods of using factor scores in statistical analysis of affective evaluation data [29,33], we defined the preference score (PS) of each fractal as its factor score on the factor Preference.

6. Data Analysis on the Effects of Physical Attributes on Preference

6.1 Effects of fractal dimension on preference

Using the PSs of the fractals, we investigated how physical attributes of the fractals influenced preference. As one of the aims of these analyses was to clarify the effects of the color attributes, i.e., hue and tone, our analyses were mainly performed on the data of the 288 chromatic fractals, that is, the fractals colored in one of the 32 BCP colors.

We first performed a two-way ANOVA to delve into how fractal dimension, when interacted with fractal style, affected PS on the 288 chromatic fractals. The results revealed a significant main effect of fractal dimension [$F(2, 279) = 25.64$, $p < .001$, $\eta^2_p = 0.16$]. Post-hoc Tukey HSD tests showed that on average, the high-dimensional fractals' PSs (M = 0.35, SD = 0.68) were higher than the intermediate-dimensional fractals' PSs (M = 0.12, SD = 1.06), p = .095, and the latter were significantly higher than the low-dimensional fractals' PSs (M = -0.42, SD = 0.90), $p < .001$. There was also a significant main effect for style [$F(2, 279 = 32.32$, $p < .001$, $\eta^2_p = 0.19$]. Post-hoc Tukey HSD tests showed that on average, PS for Koch Curve (M = 0.48, SD = 0.91) was significantly higher than for Sierpinski Carpet (M = -0.01, SD = 0.81), $p < .001$, and the latter was significantly higher than for Golden Dragon (M = -0.42, SD = 0.90), $p < .001$.

This analysis also revealed a significant two-way interaction [$F(4, 279) = 10.00$, $p < .001$, $\eta^2_p = 0.13$]. This meant that the effect of fractal dimension on PS differed across styles. Thus, we performed post-hoc Tukey HSD tests to look into how fractal dimension influenced PS respectively for each style. Figure 4(a) plots how PS varied with fractal dimension levels in terms of each fractal style.

Figure 4(a) shows that the Koch Curve style exhibited an inverted V-shaped trend. However, regarding the average PS of the intermediate-dimensional fractals, although it was significantly greater than that of the low-dimensional fractals ($p < .001$), its difference with the high-dimensional fractals' average PS was not significant (p = .683). Also, the high-dimensional fractals were significantly higher than the low-dimensional ones in average PS ($p < .001$). Thus, the general trend between fractal dimension and PS for Koch Curve fractals was an

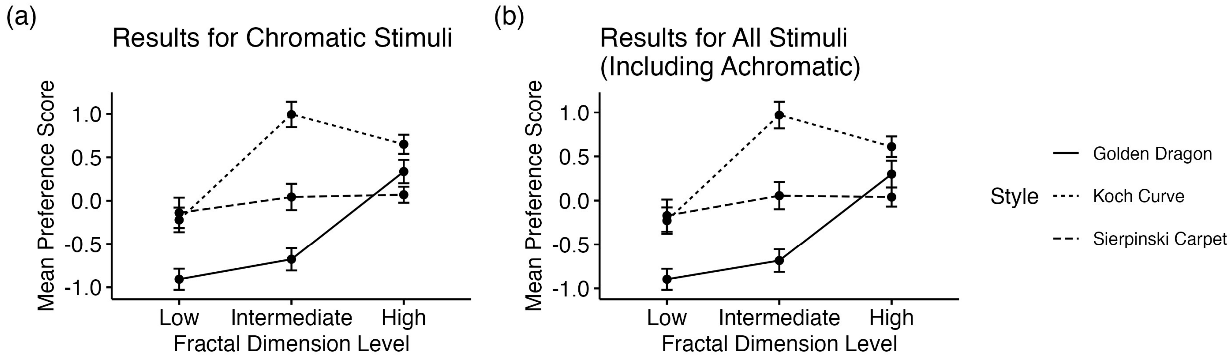

Figure 4. Changes in average preference scores across fractal dimension levels for each fractal style: (a) for the 288 chromatic fractals and (b) for all 306 fractals including achromatic ones.

ascending one. For the Sierpinski Carpet style, a weak ascending trend was discernible between fractal dimension and PS. This trend was obscure in that none of the dimension pairs had a significant difference ($ps > .970$). Regarding the Golden Dragon style, it showed an evident ascending trend in which PS increased with fractal dimension level. The high-dimensional fractals' difference with the intermediate-dimensional fractals and that with the low-dimensional fractals were significant ($ps < .001$), while the difference between the intermediate- and low-dimensional fractals did not reach significance ($p = .956$).

We then performed the same ANOVA on all 306 fractals, including the achromatic fractals. The results were nearly identical to those of the ANOVA conducted on the 288 chromatic fractals. Specifically, a significant main effect was detected for fractal dimension [$F(2, 297) = 22.22, p < .001, \eta^2_p = 0.13$]. Post-hoc Tukey HSD tests showed that the PSs of high-dimensional fractals ($M = 0.32, SD = 0.77$) were higher than those of the intermediate-dimensional fractals ($M = 0.11, SD = 1.08$), $p = .190$, and the latter were significantly higher than those of the low-dimensional fractals ($M = -0.43, SD = 0.94$), $p < .001$.

A significant main effect was also observed for style [$F(2, 297) = 28.68, p < .001, \eta^2_p = 0.16$]. Post-hoc Tukey HSD tests demonstrated that PS for Koch Curve ($M = 0.45, SD = 0.96$) was significantly higher than for Sierpinski Carpet ($M = -0.03, SD = 0.88$), $p < .001$, and the latter was significantly higher than for Golden Dragon ($M = -0.43, SD = 0.93$), $p = .002$. Additionally, a significant two-way interaction was found [$F(4, 297) = 8.71, p < .001, \eta^2_p = 0.11$].

Figure 4(b) illustrates these results, showing a strong resemblance to those in Figure 4(a). This similarity suggests that the inclusion or exclusion of achromatic fractals does not influence our findings regarding the effect of fractal dimension on PS.

6.2 Effects of color attributes on preference

Next, we investigated how the color attributes, namely hue and tone, influenced PS using the data of the chromatic fractals. We performed a two-way ANOVA that used hue and tone as factors. This analysis found a significant main effect for tone [$F(3, 256) = 60.72, p < .001, \eta^2_p = 0.42$] but not for hue [$F(7, 256) = 1.61, p = .133, \eta^2_p = 0.04$]. This meant that large differences existed among the tones. Post-hoc Tukey HSD tests showed that the tone *light* was significantly higher than any other tone ($ps < .001$), and the tone *dark* was significantly lower than any other tone ($ps < .001$). There was no significant difference between the tones *muted* and *saturated* ($p = .255$).

The results of the ANOVA also revealed a significant two-way interaction [$F(21, 256) = 2.35, p = .001, \eta^2_p = 0.16$]. This meant that different tones showed distinct patterns of how PS changed with hue. Figure 5 graphically shows this interaction, which plotted the average PS for each chromatic color. It can be observed from this figure that for the tones *light*, *saturated* and *muted*, the hues having the highest average PSs were among the warm hues (*red*, *orange*, and *yellow*) rather than the cool hues (*green*, *cyan*, and *blue*) [Note 2]. Specifically, for the tone *light*, the hue *red* had the highest average PS, which was also the highest among all colors examined in this analysis. The hue *orange* was the second highest for this tone. For the tones *saturated* and *muted*, the hue

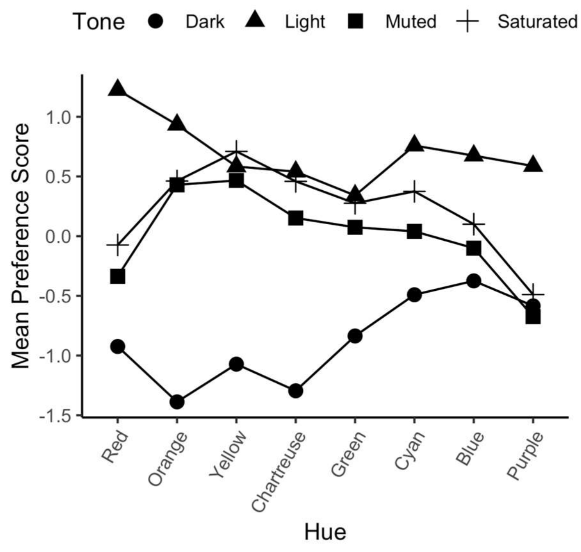

Figure 5. Changes in average preference score according to hues on each tone.

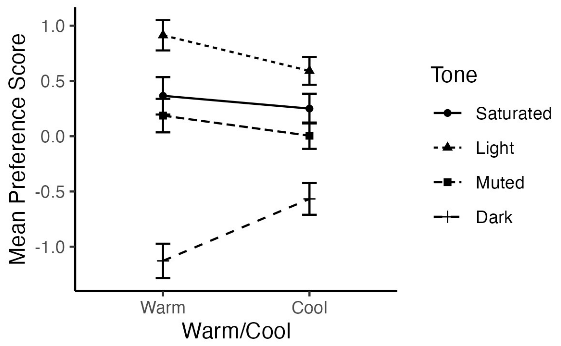

Figure 6. Comparisons of average preference scores between warm and cool hues for each tone.

yellow was the highest and *orange* followed. In contrast with these three tones, for the tone *dark*, cool hues had PSs higher than those of warm hues, in which *blue* was the highest and *cyan* was the second highest.

To further examine this pattern, we calculated the average PS for the warm hues pooled together and the average PS for the cool hues pooled together for each tone. As shown in Figure 6, for the tones *light*, *saturated*, and *muted*, the average PS of the warm hues was higher than that of the cool hues. In contrast, for the tone *dark*, the opposite trend was observed, with the cool hues having a higher average PS than the warm hues. These comparisons, along with the examinations of Figure 5, suggest that for three of the four tones (*light*, *saturated*, and *muted*), most of the warm hues were preferred than the cool hues.

However, Figure 5 also reveals an exception: for the tones *saturated* and *muted*, *red*—unlike the other two warm hues—had a lower PS than the cool hues, with an abrupt rise observed between *red* and *orange*. The underlying reasons for this phenomenon are not yet clearly understood and remain under investigation as a subject for future research.

Next, we investigated whether these effects of hue and tone varied with fractal style through a three-way ANOVA using hue, tone and fractal style as factors. The results showed a significant main effect for fractal style [$F(2, 192) = 42.77$, $p < .001$, $\eta^2_p = 0.31$] and for tone [$F(3, 192) = 70.08$, $p < .001$, $\eta^2_p = 0.52$], a marginally significant main effect for hue [$F(7, 192) = 1.86$, $p = .079$, $\eta^2_p = 0.06$], and a significant interaction between hue and tone [$F(21, 192) = 2.71$, $p < .001$, $\eta^2_p = 0.23$], which were similar to the results of the two two-way ANOVAs described above. On the other hand, none of the interactions that involved fractal style were significant [style * hue: $F(14, 192) = 0.33$, $p = .990$, $\eta^2_p = 0.02$; style * tone: $F(6, 192) = 0.36$, $p = .905$, $\eta^2_p = 0.01$; style * hue * tone: $F(42, 192) = 0.27$, $p > .999$, $\eta^2_p = 0.06$]. The non-significance of these interactions indicates that the effects of hue and tone on PS did not systematically vary across fractal styles. In other words, the influence of the combination of hue and tone on PS remained consistent across different fractal styles.

Further, we investigated whether the effects of hue and tone on PS changed with fractal dimension. We performed a three-way ANOVA that used hue, tone and fractal dimension as factors. Results showed a significant main effect for fractal dimension [$F(2, 192) = 32.08$, $p < .001$, $\eta^2_p = 0.25$] and for tone [$F(3, 192) = 66.24$, $p < .001$, $\eta^2_p = 0.51$], a close-to-significant main effect for hue [$F(7, 192) = 1.76$, $p = .099$, $\eta^2_p = 0.06$], and a significant interaction between hue and tone [$F(21, 192) = 2.56$, $p < .001$, $\eta^2_p = 0.22$]. On the other hand, none of the interactions involving fractal dimension approached statistical significance [dimension * hue: $F(14, 192) = 0.25$, $p = .997$, $\eta^2_p = 0.02$; dimension * tone: $F(6, 192) = 1.70$, $p = .124$, $\eta^2_p = 0.05$; dimension * hue * tone: $F(42, 192) = 0.22$, $p > .999$, $\eta^2_p = 0.05$]. The non-significance of these interactions means that the effects of hue and tone on PS did not systematically differ across fractal dimension levels. In other words, the pattern in which the combination of hue and tone influences PS remained stable regardless of fractal dimension levels.

7. General Discussion

7.1 Discussion on the effects of fractal dimension on preference

The first target of our data analysis was to investigate how fractal dimension influenced the preference evaluation of chromatic exact fractals, considering interactions with fractal style. From the PS data averaged across styles, we discerned an ascending trend in which average PS increased as fractal dimension level increased. This replicated the results of Bies et al.'s [6] and Robles et al.'s [7,8] studies, in which participants generally liked exact fractals of high dimension values more than those of low dimension values.

In terms of each individual fractal style investigated in our study, the Sierpinski Carpet fractals showed a weak ascending trend in which the average PS rose with the increase in dimension level (from *low* = 1.1 to *high* = 1.9). This tallied with the result of Bies et al.'s Experiment 2 [6], although the trend in Bies et al.'s study appeared stronger. Their experiment used nine fractal dimension values, spanning from 1.1 to 1.9 in increments of 0.1 (i.e., 1.1, 1.2, 1.3, ..., 1.9). They found that Sierpinski Carpet fractals' preference ratings grew higher as fractal dimension value rose across the entire range. Our result also matched that of Robles et al.'s Experiment 2 [8]. The stimuli of the experiment were a set of exact fractals called "tree-seeds", each generated by shifting the locations of the constituent parts of a Sierpinski Carpet fractal. The fractal dimension values used in their study were 1.2, 1.4, 1.6, and 1.8. Like our findings, Robles et al.'s experimental results [8] showed that the mean preference ratings for these fractals slowly increased with fractal dimension.

Regarding the Golden Dragon fractals, which had levels of recursion near 10 in this study, they showed a strong ascending trend across the three levels of fractal dimension. Bies et al.'s Experiment 2 [6] also investigated Golden Dragon fractals with 10 levels of recursion. Their results showed that between the lowest dimension value (1.1) and the intermediate dimension value (1.5), the mean preference rating increased throughout most of the range. This aligns with our finding that PS increased from the low (1.1) to the intermediate (1.5) dimension level. On the other hand, in Bies et al.'s study, the mean preference rating remained relatively stable between the intermediate (1.5) and highest (1.9) dimension values, whereas in our experiment, PS increased considerably from the intermediate (1.5) to high (1.9) dimension level. This discrepancy may be attributed to our study's use of chromatic fractals as stimuli. For the chromatic Golden Dragon fractals, high-dimensional ones possess greater degrees of elaboration and delicacy compared with intermediate-dimensional or low-dimensional ones. For high-dimensional fractals, this characteristic, along with their likeness to the appearances of foliage and vine, might remind people of decorative art crafts or jewelry designs that adopted plant themes, for example, those of Rococo or Art Nouveau styles. We speculate that this association is a possible cause of the great increase in preference for the high-dimensional Golden Dragon fractals.

Then, regarding the Koch Curve fractals, we observed a significant increase in preference from the low (1.1) to the intermediate (1.5) dimension level, followed by a slight decrease from the intermediate (1.5) to the high (1.9) dimension level. Although no previous study has ever investigated this style, Bies et al.'s Experiment 2 [6] investigated Koch Snowflake fractals each composed of three Koch Curve fractals. Their findings revealed a trend similar to ours, wherein the mean preference rating for the Snowflake fractals increased rapidly from the lowest dimension value (1.1) to 1.7—close to our intermediate dimension level (1.5)—and then slightly declined between 1.7 and the highest dimension value (1.9). These findings suggest the possibility that fractal styles similar in geometric composition have similar patterns of preference evaluation.

In conclusion, our study confirmed the general trend reported by the previous studies which stated that preference evaluation tended to be higher for exact fractals of higher dimension values. Additionally, when examining each individual fractal style, our study replicated most of the results of the previous studies. Fractal dimension value has been found to positively correlate with the health condition and immune responsiveness of some bird species [34] and the degree of maturity of some algae species [35]. Thus, we conjecture that people's general preference for exact fractals of high dimension levels may be a result of an instinctive preference for healthy and mature animals and plants, which have nutritional values for survival in natural environments.

7.2 Discussion on the effects of color attributes on preference

The next objective of the data analysis was clarifying the effects of the color attributes, namely hue and tone, on the preference evaluation, including whether the effects varied for different fractal dimension levels or styles. We compared the effects detected in our study with the results of Yokosawa et al.'s Experiment 1 [36] and Murakami et al.'s experiment [37]. Both experiments recruited Japanese participants and elicited their preference ratings for a set of digital color chips each colored in one of the 32 BCP colors. In both experiments, nearly all the *dark* colors (all except *chartreuse* in Yokosawa et al.'s experiment, and all except *blue* in Murakami et al.'s experiment) were liked less than the colors of the same hues on the other tones. Our study also observed that all hues except *purple* had their lowest average PSs on the tone *dark*. Analogous to Yokosawa et al.'s data analysis [36], for the colors belonging to tones other than *dark*, namely *light*, *saturated* and *muted*, we averaged the PSs for each color across these three tones. Then, we conducted a two-way ANOVA to compare the averaged PSs with the *dark* fractals' PSs. The results showed a significant main effect for tone [$F(1, 128) = 56.51$, $p < .001$, $\eta^2_p = 0.31$] but not for hue [$F(7, 128) = 1.68$, $p = .121$]. There was also no significant interaction between the two attributes [$F(7, 128) = 1.06$, $p = .391$]. This indicates that for any hue, *dark* was less preferred compared with the average of the other three tones. Further, Yokosawa et al. [38] compared Japanese participants, Mexican participants, and U.S. participants' preferences for the BCP colors and reported that only Japanese participants showed a dislike of dark colors. As our experiment used fractals, which are a type of stimuli different from the digital color chips used in these previous studies, our results suggest that for Japanese people, this dislike of dark colors is robust enough to appear across stimulus types.

Next, both Yokosawa et al.'s [36] and Murakami et al.'s [37] experiments reported that the Japanese participants preferred *saturated* colors to colors of other tones for most hues (all hues except *red*, *cyan* and *purple* in Yokosawa et al.'s experiment, and all hues except *cyan* and *purple* in Murakami et al.'s experiment). Our experiment found an opposite tendency in which all the *saturated* colors except *yellow* showed average PSs lower than those of the *light* colors. Another difference between our results and the previous studies' results is that in our experiment the region of warm hues is preferred over the region of cool hues on three (i.e., *light*, *saturated* and *muted*) of the four tones. Especially, the *light-red* color had the highest average PS among all colors. In contrast, for all tones in Yokosawa et al.'s experiment and all tones except *light* in Murakami et al.'s experiment, warm hues were liked less than cool hues.

We speculate that the use of fractals as stimuli in our study may be a cause of these two differences. Studies in biological morphology have reported that the coloration patterns of many species' appearances, such as animals' fur or feathers [34,39-41], insects' wings [42,43], foliage [35, 44,45] and marine macroalgae's colonies [46], possess fractal geometric features. This suggests the possibility that viewing the fractals during our experiment might have reminded the participants of their emotional experience with animals, insects or plants of such types. Thus, the reason why the participants showed relatively low preference for the *saturated* fractals may be that many creatures featuring saturated and vivid colors (e.g., toxic mushrooms and insects) are harmful or disgusting to humans. In addition, animals with skin in warm colors, such as the pink (i.e., light red) skin of an infant, often imply health and vigor. In contrast, skin in cool colors often belongs to sick or dead animals. Perhaps this is the reason why our participants preferred warm-colored over cool-colored fractals for most tones.

In brief, our study confirmed that Japanese people's dislike of dark colors also applied to chromatic exact fractals. On the other hand, saturated colors were less preferred in our study compared to previous studies. Furthermore, our participants liked warm colors more than cool colors on most tones, whereas participants in previous studies preferred cool colors to warm colors. We hypothesize that association of chromatic fractals with the appearances of certain living organisms reminded our participants of affective experiences with such organisms, which consequently influenced their preference for chromatic fractals. We plan to test this hypothesis using a new experimental paradigm that can elicit both the preference and the associated objects for chromatic fractals in future research.

8. Summary, Limitations and Future Work

This study investigated whether fractal dimension and two attributes of color, i.e., hue and tone, can influence preference for chromatic exact fractals. Through Experiment 1, we established the SD scales for affective evaluations of exact fractals. Experiment 2 elicited participants' affective evaluations for exact fractals using these scales. A factor analysis found that the evaluations were composed of four main factors, one representing preference. Data analyses generally replicated the ascending trend between preference rating and fractal dimension level reported by previous studies. Regarding the effects of color on preference, we found that Japanese people's dislike of dark colors extended to their impressions of chromatic exact fractals. However, the saturated colors were liked less than in previous studies. Also, contrary to previous studies' reports, our participants exhibited a greater preference for fractals of warm hues than for fractals of cool hues on most tones. We speculate that association of chromatic exact fractals with the appearances of some biological species possibly caused the differences between our results and those of previous studies. As explained at the end of Section 7.2, we plan to design new experiments to verify this hypothesis.

Although the sample size and the number of participants for rating the affective-evaluation scales are both sufficiently large (as described in Sections 2 and 4.2), a limitation remains in that the participants lacked cultural diversity. This suggests a need to conduct experiments that recruit participants from different countries or cultural backgrounds. We are particularly interested in comparing experimental results across countries and cultures to assess the degree of universality and variation in the effects observed in this study.

Another limitation is that chroma and lightness of the colors were incorporated into a single attribute (i.e., tone) which impeded the understanding of their respective effects. Because using two color variables instead of one would significantly increase the number of trials, making an experiment too fatiguing for participants, we are considering designing a series of experiments, each investigating a subset of the colors.

The next step of the research also includes analyzing the impacts of fractal dimension and color attributes on the other factors of affective evaluations, that is, Weightiness, Toughness and Complexity, as well as the interactions among the factors. Further, as categorical prototypicality has been reported to influence preference for colors [47] and paintings [48,49], we consider it important to explore whether exact fractals' prototypicality in terms of their respective styles can affect preference for exact fractals.

Notes

1. Parts of this study were presented at the 23rd Annual Meeting of the Japan Society of Kansei Engineering [50].
2. As the remaining two hues, *chartreuse* and *purple*, are between warm and cool hues, they are considered *neutral* hues in this study.

Reference

[1] Trochet, H., A History of Fractal Geometry, MacTutor, 2009, February, https://mathshistory.st-andrews.ac.uk/HistTopics/fractals/

[2] Anguera, J., Andújar, A., Jayasinghe, J., Chakravarthy, V. V. S. S. S., Chowdary, P. S. R., Pijoan, J. L., Ali, T., & Cattani, C., Fractal Antennas: An Historical Perspective, Fractal and Fractional, Vol. 4, No. 1, 3, 2020.

[3] Mandelbrot, B. B., Fractal Geometry: What is it, and What does it do? Proceedings of the Royal Society of London. A. Mathematical and Physical Sciences, Vol. 423, No. 1864, pp. 3-16, 1989.

[4] Ashlock, D., & Jamieson, B., Evolutionary Computation to Search Mandelbrot Sets for Aesthetic Images, Journal of Mathematics and the Arts, Vol. 1, No. 3, pp. 147-158, 2007.

[5] Hagerhall, C. M., Laike, T., Küller, M., Marcheschi, E., Boydston, C., & Taylor, R. P., Human Physiological Benefits of Viewing Nature: EEG Responses to Exact and Statistical Fractal Patterns, Nonlinear Dynamics, Psychology, and Life Sciences, Vol. 19, No. 1, pp. 1-12, 2015.

[6] Bies, A. J., Blanc-Goldhammer, D. R., Boydston, C. R., Taylor, R. P., & Sereno, M. E., Aesthetic Responses to Exact Fractals Driven by Physical Complexity, Frontiers in Human Neuroscience, No. 10, 210, 2016.

[7] Robles, K. E., Liaw, N. A., Taylor, R. P., Baldwin, D. A., & Sereno, M. E., A Shared Fractal Aesthetic Across Development, Humanities and Social Sciences Communications, Vol. 7, No. 1, 158, 2020.

[8] Robles, K. E., Roberts, M., Viengkham, C., Smith, J. H., Rowland, C., Moslehi, S., Stadlober, S., Lesjak, A., Lesjak, M., Taylor, R. P., Spehar, B., & Sereno, M. E., Aesthetics and Psychological Effects of Fractal Based Design, Frontiers in Psychology, Vol. 12, 699962, 2021.

[9] Hausser, M., Fascinating Fractal Wall Art, Matthias Hauser Wall Art, n.d., https://matthias-hauser.pixels.com/collections/fascinating+fractals

[10] Sekino, J., Stories about Fractal Art, Sekino's Art World, n.d., https://www.sekinoworld.com/fractal/#story

[11] Zare, R., Fractal Miniatures, Roger Zare Composer, n.d., https://rogerzare.com/fractal_miniatures.htm

[12] Comrey, A. L., & Lee, H. B., A First Course in Factor Analysis

(2nd ed.), Lawrence Erlbaum Associates, Inc., 1992, Transferred to Digital Printing by Psychology Press, Taylor & Francis Group, 2009.

[13] Watson, P., Generalizability and Sample Size in EFA and PCA, MRC Cognition and Brain Sciences Unit, University of Cambridge, 2014, https://imaging.mrc-cbu.cam.ac.uk/statswiki/FAQ/RatCaseVar

[14] Nunnally, J. C., Psychometric Theory (2nd ed.), MaGraw-Hill, 1978.

[15] Everitt, B. S., Multivariate Analysis: The Need for Data, and Other Problems, The British Journal of Psychiatry, Vol. 126, No. 3, pp. 237-240, 1975.

[16] Lingl, G., Turtle − Turtle Graphics, 2009, https://docs.python.org/3/library/turtle.html

[17] Pygame, .n.d., https://www.pygame.org/docs/

[18] Geeksforgeeks, Koch Curve or Koch Snowflake, 2018, https://www.geeksforgeeks.org/koch-curve-koch-snowflake/

[19] Iida, K., Fractal: A General Purpose Architecture for Estimating the Fractal Dimension of Any Pattern or Geometry, 2016, https://github.com/kaziida24/fractal

[20] Palmer, S. E., & Schloss, K. B., An Ecological Valence Theory of Human Color Preference, Proceedings of the National Academy of Sciences, Vol. 107, No. 19, pp. 8877-8882, 2010.

[21] Palmer, S. E., & Schloss, K. B., Human Preference for Individual Colors. In: Human Vision and Electronic Imaging XV (Vol. 7527, pp. 353-364), SPIE, 2010.

[22] Fukuda, T., & Fukuda, R., Ningen Kogaku Gaido: Kansei o Kagakusuru Hoho (Zohoban) [Introductory Ergonomics: A Scientific Approach to Kansei (extended ed.)], Saiensu-Sha, 2009. (in Japanese)

[23] Okajima, T., Kubo, T., Noda, K., & Fujibayashi, K., A Special Analysis of Stripes and its Application to Visual Effects of Architectural Stripe Patterns, Journal of Structural and Construction Engineering (Transactions of Architectural Institute of Japan), Vol. 356, pp. 16-23, 1985. (in Japanese)

[24] Okajima, T., Hayashi, Y., Konishi, H., & Noda, K., Fractal Stripe Pattern and its Psychological Effect, Journal of Structural and Construction Engineering (Transactions of Architectural Institute of Japan), Vol. 372, pp. 1-9, 1987. (in Japanese)

[25] Cho, K., & Haraguchi, M., Order and Evaluation of Paintings: Approach from Kansei Psychology (2). In: Proceedings of the 11th Conference of the Japanese Society for Cognitive Psychology (p. 132), The Japanese Society for Cognitive Psychology, 2013. (in Japanese)

[26] Cho, K., Haraguchi, M., & Miura. K., Relationship Between Fractal in Paintings and Aesthetic Evaluations. In: Proceedings of the 13th Conference of the Japanese Society for Cognitive Psychology (p. 159), The Japanese Society for Cognitive Psychology, 2015. (in Japanese)

[27] Kato., U. Psychological and Physiological Responses to Two-Color Combination, Journal of the Color Science Association of Japan, Vol, 29, No, 3, pp. 210-219, 2005. (in Japanese)

[28] Tsutsui, A., & Ohmi, G., Pleasantness, Interestingness and Color Affective Scales in Color Combinations, Bulletin of Japanese Society for the Science of Design, Vol. 56, No. 3, pp. 81-88, 2009. (in Japanese)

[29] Fang, S., Muramatsu, K., & Matsui, T., A Computational Model Simulating the Mental Function of Multicolor Aesthetic Evaluation, Color Research & Application, Vol. 42, No. 2, pp. 216-235, 2017.

[30] Ou, L., Luo, M. R., Woodcock, A., & Wright, A., A Study of Colour Emotion and Colour Preference. Part I: Colour Emotions for Single Colours, Color Research & Application, Vol. 29, No. 3, pp. 232-240, 2004.

[31] Robinson, J. P., Shaver, P. R., & Wrightsman, L. S., Criteria for Scale Selection and Evaluation, In: J. P. Robinson, P. R. Shaver, & L. S. Wrightsman (Eds.), Measures of Personality and Social Psychological Attitudes (pp. 1-16), Academic Press, Inc., 1991.

[32] Cho, K., & Haraguchi, M., Scale Construction of Adjective Pairs on the Research of Impression of Paintings (2), Kurume University of Psychological Research, Vol. 13, pp. 45-53, 2014. (in Japanese)

[33] Fang, S., Muramatsu, K., & Matsui, T., Experimental Study of Aesthetic Evaluation to Multi-Color Stimuli Using Semantic Differential Method: Towards the Construction of an Artificial KANSEI System, Transactions of Japan Society of Kansei Engineering, Vol. 14, No. 1, pp. 37-47, 2015.

[34] Pérez-Rodríguez, L., Jovani, R., & Mougeot, F., Fractal Geometry of a Complex Plumage Trait Reveals Bird's Quality, Proceedings of the Royal Society B: Biological Sciences, Vol. 280, No. 1755, 20122783, 2013.

[35] Corbit, J. D., & Garbary, D. J., Fractal Dimension as a Quantitative Measure of Complexity in Plant Development, Proceedings of the Royal Society of London. Series B: Biological Sciences, Vol. 262, No. 1363, pp. 1-6, 1995.

[36] Yokosawa, K., Schloss, K. B., Asano, M., & Palmer, S. E., Ecological Effects in Cross-Cultural Differences Between U.S. and Japanese Color Preferences, Cognitive Science, Vol. 40, No. 7, pp. 1590-1616, 2016.

[37] Murakami, H., Izawa, R., Nishiyama, Y., & Akiyoshi, M., Does Color Preference Affect Sense of Agency over Voluntary Action? Proceedings of the 35th Annual Meeting of the Japanese Cognitive Science Society (pp. 512-515), 2018. (in Japanese)

[38] Yokosawa, K., Yano, N., Schloss, K. B., Prado-Leon, L. R., & Palmer, S. E., Cross-Cultural Studies of Color Preferences: US, Japan, and Mexico, Journal of Vision, Vol. 10, No. 7, 408, 2010 (with Poster: https://palmerlab.berkeley.edu/pdf/Yokosawa-VSS2010.pdf)

[39] Galipot, P., And Growth on Form? How Tissue Expansion Generates Novel Shapes, Colours and Enhance Biological Functions of Turing Colour Patterns of Eukaryotes, bioRxiv, 2023.02.16.528816, 2023.

[40] Pérez-Rodríguez, L., Jovani, R., & Stevens, M., Shape Matters: Animal Colour Patterns as Signals of Individual Quality, Proceedings of the Royal Society B: Biological Sciences, Vol. 284, No. 1849, 20162446, 2017.

[41] Stoddard, M. C., & Osorio, D., Animal Coloration Patterns:

Linking Spatial Vision to Quantitative Analysis, The American Naturalist, Vol. 193, No. 2, pp. 164-186, 2019.
[42] Otaki, J. M., The Fractal Geometry of the Nymphalid Groundplan: Self-Similar Configuration of Color Pattern Symmetry Systems in Butterfly Wings, Insects, Vol. 12, No. 1, 39, 2021.
[43] Schubnel, T., Mazurier, A., Nel, A., Grandcolas, P., Desutter-Grandcolas, L., Legendre, F., & Garrouste, R., Flat does not Mean 2D: Using X-Ray Microtomography to Study Insect Wings in 3D as a Model for Comparative Studies, Methods in Ecology and Evolution, Vol. 14, No. 8, pp. 2036-2048, 2023.
[44] Boudon, F., Godin, C., Pradal, C., Puech, O., & Sinoquet, H., Estimating the Fractal Dimension of Plants Using the Two-Surface Method: An Analysis Based on 3D-Digitized Tree Foliage, Fractals, Vol. 14, No. 3, pp. 149-163, 2006.
[45] Matos, R. S., Ţălu, Ş., Mota, G. V. S., Pinto, E. P., Pires, M. A., Abraçado, L. G., & Ferreira, N. S., Correlating Structure and Morphology of Andiroba Leaf (Carapa Guianensis Aubl.) by Microscopy and Fractal Theory Analyses, Applied Sciences, Vol. 11, No. 13, 5848, 2021.
[46] Gee, J., & Warwick, R., Metazoan Community Structure in Relation to the Fractal Dimensions of Marine Macroalgae, Marine Ecology Progress Series, Vol. 103, pp. 141-150, 1994.
[47] Fang, S., Tawatsuji, Y., & Matsui, T., An Appraisal of Gracefulness Mediates the Negative Influence of Color Focality on Color Preference in Japan, International Journal of Affective Engineering, Vol. 21, No. 1, pp. 1-11, 2022.
[48] Ogata, S. F., Tawatsuji, Y., & Matsui, T., Using a Drift Diffusion Model to Validate the Quantification of Style Prototypicality as Assessed by the Viewers of Paintings, Leonardo, Vol. 57, No. 1, pp. 70-78, 2024.
[49] Ogata, S. F., Tawatsuji, Y., & Matsui, T., Exploratory Research on Influences of Style-Based Categorization on Affective Evaluations of Paintings, International Journal of Affective Engineering, Vol. 23, No. 1, pp. 49-62, 2024.
[50] Bi, Y., Fang, S., & Matsui, T., A Quantitative Study on Influences of Fractal Dimension and Color Attributes on Affective Evaluation of Fractal Patterns [Conference Presentation], The 23rd Annual Meeting of the Japan Society of Kansei Engineering, Online Conference, 2021, September 2-4. (in Japanese)

Shigen Fang Ogata is an assistant professor in information science at the Graduate School of Education, Hyogo University of Teacher Education. He received Ph.D. in Human Sciences from Waseda University in 2018. After graduation, he worked as a research associate and then an assistant professor in data science at the Global Education Center, Waseda University. He joined Hyogo University of Teacher Education in 2022. His research interests include affective computing of visual information, and interactions between human and AI arts. He is a member of the Society for Art and Science, the Japanese Cognitive Science Society, the Japanese Society for Artificial Intelligence, and the American Psychological Association (APA).

Yiyang Bi is a data engineer working in Houston, Texas, the United States of America. She received a bachelor's degree from the School of Human Sciences at Waseda University in 2022 and a master's degree in data science from University of California San Diego in 2024. Her research interests include data analysis in human emotions and affects, database management, and data warehousing. She has experience in data pipeline construction using SQL and Azure, supply chain optimization, and AI for traffic accident recognition.

Tatsunori Matsui is a professor of the Faculty of Human Sciences, Waseda University and a Dr. of Science. He graduated from the School of Science and Engineering at Waseda University in 1988, and completed his doctorate at the Graduate School of Science and Engineering, Waseda University in 1994. After working as an assistant professor at Tokyo Gakugei University, an associate professor at the Graduate School of Information Systems, the University of Electro-Communications, and an associate professor at the Faculty of Human Sciences, Waseda University, he was appointed to his current position in 2007. He has engaged in research on Artificial Intelligence in Education, Affective Computing for Learning, and Kansei Information Science. He is the vice president of the Association for Information Science in Educational Systems and the president of the Learning Analysis Society of Japan.