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Abstract Shape Aesthetics: Contour, Complexity, Motion, and Individual Variability

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Abstract

The aesthetics of abstract shapes — shapes devoid of meaning or familiarity — offer an intriguing subject for study, as it can offer insights into how we perceive and appreciate visual stimuli, shedding light on the underlying mechanisms of visual cognition and the nature of artistic experience. This research investigates the impact of contour type (angular versus rounded edges) and complexity (number of vertices) on aesthetic preferences, including their potential interaction. Additionally, we explored the influence of movement as an aesthetic variable, given its potential to enhance complexity, though the relationship between movement and complexity remains unexplored. Our findings indicate that both contour type and complexity significantly influence preferences, with shapes featuring curved contours and fewer vertices being favoured. This highlights the aesthetic appeal of curvature and simplicity. Contrary to expectations, movement did not have a noticeable effect on aesthetic judgements. While no overall interaction between contour type and complexity was found, this lack of interaction was obscured by significant individual differences. Specifically, within individuals, strong interactions between contour type and complexity were observed. It appears that these individual differences are due more to the varying emphasis (dominance) placed on each variable rather than a difference in the preference for specific characteristics. Future research should further analyse these individual differences to understand the nuanced dynamics of aesthetic preferences.

Keywords

aesthetics, individual differences, curvature, contour, complexity, movement, abstract shapes

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1. Introduction

Understanding the psychological basis of aesthetics has long been a central pursuit spanning fields from philosophy to psychology and design. However, several questions around key drivers of appeal remain unresolved. It was in 1876 that Fechner described empirical methods for measuring aesthetic preferences. This empirical approach to aesthetics is general because it deals with all preferences, including preferences for everyday objects and abstract shapes. At the same time, the study of preferences is also narrower than the broader field of aesthetics, because in experimental aesthetics we are not trying to capture the essence of aesthetic experience or, if it exists, the sublime.

With this approach it is possible to evaluate hypotheses about preference for certain properties of shapes, called aesthetic variables. Examples of properties measured and manipulated include visual symmetry (symmetric shapes are favoured over asymmetric ones; Bertamini *et al.*, 2019; Eisenman, 1967), contour type (curvature is favoured over angularity; Bar and Neta, 2006; Bertamini *et al.*, 2015; Corradi *et al.*, 2019; Palumbo *et al.*, 2022), colours (dark shades are usually disliked relative to lighter shades; Guilford and Smith, 1959; Palmer and Schloss, 2010), spatial frequency (patterns for which we have higher sensitivity are preferred over patterns for which we are less sensitive; Mather, 2014; Spehar *et al.*, 2015), complexity (a medium level of complexity is favoured over higher or lower levels of complexity; Berlyne, 1971).

Although the literature identifies preferences for certain properties, universally preferred properties are rare. Aesthetic experiences are largely subjective and vary among individuals. Therefore, understanding the factors contributing to individual differences is crucial, as it provides insights into the psychological, cultural, and neurological foundations of aesthetic perception and appreciation (Jacobsen, 2010).

This study examines contour type, complexity, and motion of abstract shapes and considers individual differences. In contour type, the key factor influencing preference is curvature over angularity. Although Bar and Neta (2006) hypothesised that the preference is triggered by an avoidance response to angularity, later findings have confirmed a preference for curvature even when the stimuli do not contain angles (Bertamini *et al.*, 2015).

Complexity is a difficult dimension to define and quantify (Nadal *et al.*, 2010). In an early attempt to capture the role of complexity, the mathematician Birkhoff (1933) proposed that aesthetic value should decrease with complexity because complexity implies effort. He suggested that polygon complexity is related to the number of independent straight lines that contain the shape. However, other authors have proposed different approaches. For Eysenck (1942), aesthetic value should increase with complexity. He found some support for this pattern in his studies. By contrast, Berlyne (1971) predicted, based on theoretical considerations, that preference should peak at intermediate levels of complexity. However, the empirical evidence is mixed.

With regards to movement, a framework is necessary. A moving shape may be considered as more complex than a static shape. Hence, it is unclear whether movement is an independent variable, potentially affecting aesthetics or whether it is a component of complexity, affecting aesthetics indirectly. The current study will clarify this issue. Although movement as an aesthetic feature has not been extensively studied as contour type and complexity, there is evidence that it can influence aesthetics, as the next section specifies.

1.1. Effect of Movement on Aesthetic Preferences

Movement's captivating power has been examined from various psychological perspectives. Researchers have analysed the low-level involuntary responses to motion that capture attention more effectively than static stimuli (Franconeri and Simons, 2003) as well as the higher-level cognitive factors that play a role in the aesthetic evaluation of dynamic phenomena (Santayana, 1896/2019).

Artists intuitively leverage movement principles to direct viewer attention, heighten drama and inject life into their works. Techniques like diagonal lines, S-curves and the implied motion captured in a freeze-frame-like moment are visually captivating and stimulate aesthetic wonder (Arnheim, 1974). While aesthetic judgements of movement manifest differently across cultures (Freedberg and Gallese, 2007), researchers generally agree human and nonhuman animals share an innate sensitivity to motion (Butler, 1954; Cohen, 1969; Flavell *et al.*, 2019; Petrelli *et al.*, 2016; Soranzo *et al.*, 2018; Wright and Bertamini, 2015). However, the appeal of unfamiliar moving shapes has not been extensively explored so far.

One of the objectives of this research is to assess whether abstract shapes are perceived as more aesthetically pleasing when in motion. This section reviews studies where a preference for moving stimuli emerged, even if it was not the primary objective of their research. A preference for moving stimuli has been observed in nonhuman animals as well as in infants and adults.

1.2. Nonhuman Animals

Butler (1954) conducted an experiment on monkeys to measure visual exploratory behaviour. The results showed that the monkeys' response frequency was highest when viewing another monkey. It progressively decreased under other conditions such as viewing a moving electric train, a bowl of food, and an empty incentive chamber. Of relevance to this study is the comparison between the electric train (a dynamic and unappealing object) and the array of food (a static and appealing object). Assuming that the time spent looking at stimuli correlates with their appeal, it can be inferred that monkeys prefer moving inedible objects over appetising static objects. This is ultimately a preference for dynamic stimuli.

1.3. Human Infants

Cohen (1969) found that 2–6-months-old human infants tend to prefer moving stimuli over stationary ones using a time fixation paradigm. This paradigm is a powerful tool for studying infant cognition as it provides insight into their perceptual abilities and preferences (Colombo and Mitchell, 2009). It consists of presenting a salient visual stimulus to an infant against a background. The infant's orientation response is measured through 'looking time', which is the total duration of fixation on the stimulus (Aerdker *et al.*, 2022).

In Cohen's (1969) study, stimulation consisted of a blinking light that randomly changed position in a 4×4 light matrix. Infants were found to prefer lights that changed position over a stationary light, with the greatest preference occurring in the early trials when the light varied among four matrix positions and in the late trials when the light varied among 16 positions. Moreover, lights with more position changes were preferred (indicating less habituation) over lights with fewer position changes.

1.4. Human Adults

Wright and Bertamini (2005) used symmetrical or random line moving configurations. Each line element had a local rotation, and the whole configuration underwent a global transformation (horizontal translation, rotation, expansion, horizontal shear). Dynamic symmetrical patterns were preferred to random patterns. Of the global transformations, observers liked expansion the most and horizontal shear the least. Soranzo *et al.* (2018) found that Interactive Objects (IOs, three-dimensional physical artefacts that exhibit autonomous behaviour, such as lighting up, sounding or vibrating, when touched) are preferred over static, quiescent objects. The authors interpret these findings considering arousal. It is known that aesthetics is positively correlated with arousal (Marković, 2012). IOs share with moving stimuli a temporal change: moving stimuli change spatial position over time, IOs change state over time. These stimuli enhance arousal, which, in turn, enhances aesthetics.

This paper aims at clarifying the interplay between contour type, complexity, and movement for abstract shapes; hence, avoiding familiarity and semantics. The investigation of the interplay between different variables is a relatively emerging area of research (Makin, 2017; Marković and Gvozdenovi, 2001). Most existing research focuses on one primary variable while holding others constant. In this research we aim at clarifying whether different variables interact with each other in relation to their effects on aesthetics. One of the most interesting things about studying different variables at the same time is that we can assess not only the preference for certain properties of the stimuli but also what Gao and Soranzo (2020) define as *dominance*, which is the relative importance of a variable. Therefore, we use the noun *preference* to indicate the preference for one level over another within a given variable (e.g., preference for curvature over angularity) and the noun dominance to indicate which variable is more effective when making an aesthetic judgement (e.g., evaluating the aesthetics of a stimulus on the basis of its complexity rather than its contour). To determine dominance, more than one variable must be examined simultaneously. As we shall see, the distinction between preference and dominance becomes paramount when considering individual differences.

1.5. Rationale

The aesthetic effects of contour type, complexity, and movement, as reviewed in the Introduction, have largely been studied independently. We hypothesise that most people will prefer smooth curvature. We also predict an overall preference for complexity and movement, though these factors may be context-dependent. According to Berlyne (1971), an intermediate level of complexity is typically preferred, but identifying this level for abstract shapes is challenging. Simple shapes like circles and squares might be preferred due to their simplicity and familiarity.

Orientation was included as a variable to avoid biasing the results by fixing it at one level, but we do not expect preferences to differ among orientations of 0, 45, and 90 degrees.

The primary aim of this study is to assess the interaction between contour type, complexity, and movement, evaluating both preferences and the relative importance (dominance) of these factors in aesthetic judgement. Additionally, we seek to determine whether movement acts as a component of complexity or influences aesthetics independently.

Finally, we aim to investigate whether the aesthetic impact of movement observed in studies with real and meaningful objects extends to abstract shapes. This will help determine the generalizability of movement's aesthetic effects. Thus, the rationale of this study is to explore the interactions between contour type, complexity, and movement in shaping aesthetic preferences.

2. Experiment

2.1. Participants

Fifty-one participants (41 females and 10 males, mean age 36.37) were recruited for the experiment. All participants had normal or corrected-to-normal vision. The experiment was conducted in accordance with the Declaration of Helsinki (2008) and received ethics approval. Participation was voluntary and no remuneration was provided.

2.2. *Materials and Methods*

2.2.1. *Stimuli*

Abstract and meaningless shapes presented on a computer screen were utilised as stimuli. They were selected from those used by Bertamini *et al.* (2015) in experiment 1 and movement was added to some conditions. Python and PsychoPy were used to create the experiment (Peirce, 2007). Thirty-six lobed oval shapes were employed as stimuli, resulting from the combinations of the following independent variables:

- Contour type — two levels: curved and angular;
- Complexity — two levels: six and 22 vertices;
- Movement — three levels: static, expanding, and rotating;
- Orientation — three levels: 0, 45 and 90 degrees.

Figure 1A shows the stimuli used in the experiment at the static level of the movement variable. In addition to the static version, each stimulus moved in two ways: expanding and rotating. These specific movements allow a fair comparison with the corresponding static stimuli because moving stimuli remain in the same position as the static stimuli, at the screen centre. Furthermore, expansion and rotation allow one to control for the effect of size. Silvera *et al.* (2002) found that larger stimuli are generally preferred to smaller stimuli. To control for this potential confounding variable, the dynamic stimuli had the same average size (over time) as the corresponding static stimuli. In particular, expanding stimuli were programmed in such a way that after each cycle of expansion/shrinkage, the average size was the same as that of the static stimuli. With respect to speed, we chose events that lasted a few seconds, with movements well above threshold. Hence, an expansion/shrinkage cycle lasted 8 s. Similarly, a complete rotation lasted 8 s.

Stimuli were presented in random order on a grey background whose luminance was approximately 56 cd/m^2. Together with the stimuli, a slider was presented for the participants to provide their aesthetic ratings using the mouse (Fig. 1B).

2.2.2. *Procedure*

The participants sat in a darkened cubicle 57 cm from a 29 × 53 cm LCD monitor. The experiment stimulus was controlled using PsychoPy software (Peirce,

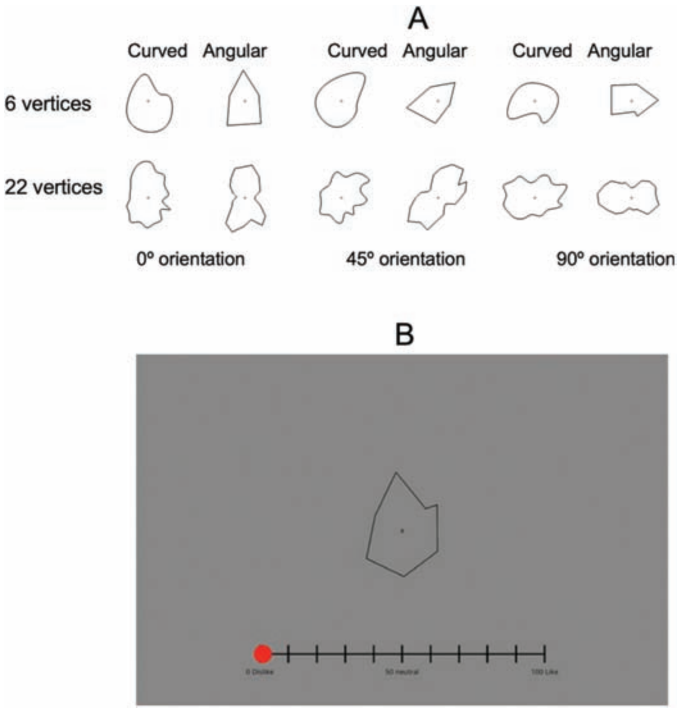

Figure 1. (A) Stimuli used in the experiment organised by Complexity (rows), by Contour type and Orientation (columns). (B) Example of stimulus presentation. Together with a stimulus, participants were presented with a slider that could be adjusted by means of the mouse.

2007). Participants entered their responses by sliding the slider with a mouse. Different stimuli were generated randomly each time. Each condition was presented three times, making a total of 108 stimuli presentations per participant ($2\times2\times3\times3\times3$). The experiment lasted about 16 minutes.

3. Results

Figure 2 shows the aesthetics ratings averages with Contour type on the x-axis and Movement in the legend. Averages are grouped in two panels according to Complexity.

As can be seen from the figure, aesthetics ratings were higher in the curved level of Contour, compared to the angular level. Furthermore, aesthetics ratings were higher in the six vertices level, compared to the 22 vertices level. No additional pattern seems to emerge from the figure.

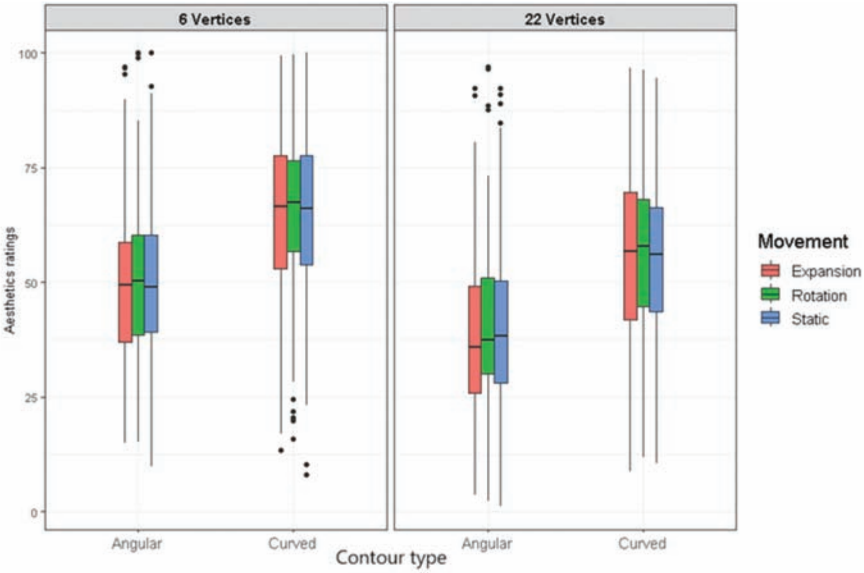

Figure 2. Aesthetics ratings with Contour type on the x-axis and Movement in the legend. Left panel: low Complexity. Right panel: high Complexity.

3.1. Analysis

The data were analysed using Bayesian mixed-effects models. These models were created in the Stan computational framework (Carpenter *et al.*, 2017) and accessed using the high-level interface brms package 2.10.0 (Bürkner, 2017) with the gaussian family distribution run in R (R Core Team, 2022). Weakly informative priors (the default priors of the brms function) were set for intercept and population-level effects.

The model estimation used four chains with 2000 iterations, of which 1000 warmups, and 4000 post warm-up samples. Model diagnostics were checked via convergence statistics (R_{hat} close to or equal to 1.0) and visual inspection of the trace plots. All credible intervals were the Highest Density Intervals [HDIs (see Note 1); Box and Tiao, 1992; Chen *et al.*, 2000; Hespanhol *et al.*, 2019].

The Bayesian approach was chosen without relying on the Bayes factors for a decision concerning experimental hypothesis (Kruschke and Liddell, 2018; Van der Linden and Chryst, 2017). This approach was also chosen to avoid the statistical peculiarities of null hypothesis significance testing, for instance, the dependence on predefined sampling plans (Gelman et al., 1995; McShane et al., 2019; Wagenmakers, 2007). This approach allows conclusions based on a null effect (Dienes, 2014), which is particularly useful in the context of this project as a null effect of Orientation was predicted.

To assess the hypothesis that the variable Orientation did not affect ratings, a preliminary analysis was run using Orientation as the only population-level variable. Results shown in Table 1 support the hypothesis that this variable is not affecting ratings and was therefore added as a group-level effect in the subsequent models, as a further repetition of the same stimulus.

The variables Contour Type, Complexity, Movement — together with their interactions — were inputted as population-level (or fixed) factors and the variable Participant as a group-level (or random) factor.

To assess the hypothesis that there is a common slope for all participants, we fit two models, one with and one without group-level slopes for the type of Contour, Complexity and Movement (both including random intercepts). Comparing the two models on Pareto-smoothed importance-sampling leave-one-out cross-validation (PSIS-LOO; Vehtari et al., 2024) reveals an estimated difference in expected log pointwise predictive density (elpd) of 1310.6 (with a standard error of 47.7 — Note 2) in favour of the model including group-level slopes, indicating large individual differences.

As can be seen in Table 2, an effect of Contour type emerges with an estimate preference for curved stimuli of 15.13 points on the rating scale (std error = 2.98) over angular stimuli. A negative effect of Complexity (i.e., an effect of simplicity) also emerges, with stimuli of 22 vertices receiving an estimate of 10.7 ratings (std error = 3.55) less than the corresponding six-vertices stimuli. Lower and upper credible intervals for these two variables do not include 0, indicating that these variables affect ratings. Movement, instead, did not show any effect, and the inclusion of 0 in the credible intervals does not support the hypothesis that this variable affects aesthetics ratings. Moreover, no effects emerged from the interactions among these variables. As we shall see, this apparent lack of interaction effects is highly informative as it evidences important individual differences.

Table 1. Estimated effect of orientation and credible intervals on aesthetics ratings.

Predictors	Estimates	Std error	CI (95%)
Intercept	52.61	0.81	51.02–54.17
Orientation45d	−0.22	1.16	−2.55–1.98
Orientation90d	−0.32	1.16	−2.58–2.05

Table 2. Estimate of population level effects, estimated error and credible intervals.

Predictors	Estimates	Std error	CI (95%)
Intercept	49.34	2.23	45.09–53.77
Contour	15.13	2.98	9.21–21.44
Complexity	−10.70	3.55	−17.57–4.23
Movementrot	0.78	1.08	−1.32–2.89
Movementstatic	0.35	1.18	−2.09–2.80
Contour:Complexity	1.96	2.57	−3.30–7.10
Contour:Movementrot	0.65	1.22	−1.83–3.06
Contour:Movementstatic	0.05	1.33	−2.55–2.85
Complexity:Movementrot	0.51	1.34	−2.04–3.07
Complexity:Movementstatic	0.67	1.30	−1.91–3.18
Contour:Complexity:Movementrot	−1.31	1.70	−4.79–2.01
Contour:Complexity:Movementstatic	−2.52	1.75	−5.98–1.04

3.2. Model Evaluation

The full model specifications were assessed using a posterior predictive check. This analysis compared the simulated data generated from the model with the actual data.

Figure 3 displays the 95% posterior credible intervals (indicated by light lines) of the ratings for the variables Contour type (left), Complexity (middle), and Movement (right). These represent newly generated hypothetical data using posterior distribution parameters. The dark line in each plot represents the probability of the actual data. No major systematic discrepancies emerge

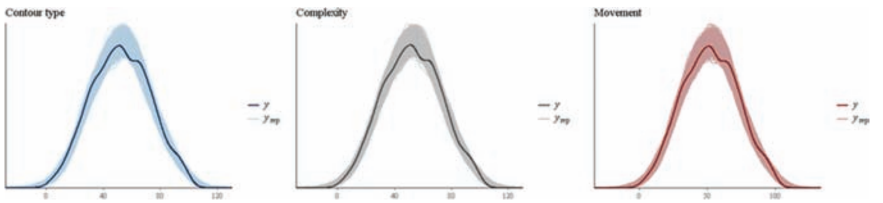

Figure 3. Posterior predictive check for the Bayesian model. The plots illustrate the comparison between observed data and data simulated from the posterior predictive distribution of the model and the actual data. They provide an assessment of the model's adequacy in capturing the observed data patterns. No major systematic discrepancies emerge based on model predictions.

based on model predictions, suggesting that the model is an adequate fit for the data.

3.3. Analysis of Individual Differences

While the aggregate data revealed clear aesthetic preferences for curved — rather than angular — contours, and for simple — rather than complex — stimuli (but not for their interaction) and an obvious lack of preference for moving shapes, a closer inspection of the range of participants' responses is important (Mallon *et al.*, 2014). In this section we report individual differences for the three variables considered and the interaction between contour type and complexity.

3.3.1. Individual Differences: Contour Type

To assess the individual differences of Contour type, we extracted from the Bayesian model the random slopes of this variable and added its estimated fixed effect (15.13, see Table 2). In this way, negative estimates indicate a preference for angular contours while positive values indicate a preference for curved contours. These estimates are represented by a dot in Fig. 4. The figure also shows, for each participant, the 95% credible interval of the estimates; these are represented by a horizontal line. Credible intervals intersecting with zero (crossed by the vertical red dashed line) indicate that for these participants the two types of contours were practically the same from an aesthetic point of view.

As can be seen from the figure, under our experimental conditions, the preference for curvature over angularity is shared amongst most of the participants. Only P13, P45 and P50 preferred angularity while few participants did not show any preference. In sum, it seems that the preference for curved shapes is robust and extends to most participants, with just a few exceptions.

3.3.2. Individual Differences: Complexity

Similarly to the contour analysis, to explore the individual differences of Complexity, we extracted from the Bayesian model the random slopes and added the estimated fixed effect (−10.7, see Table 2). In this way, negative estimates indicate a preference for shapes with six vertices while positive values indicate a preference for 22 vertices shapes. These estimates are represented by a dot in Fig. 5. Figure 5 also shows, for each participant, the 95% credible interval of the estimates; these are represented by a horizontal line. Credible intervals intersecting with zero (crossed by the vertical red dashed line) indicate that for these participants the two types of complexities were practically the same from an aesthetic point of view.

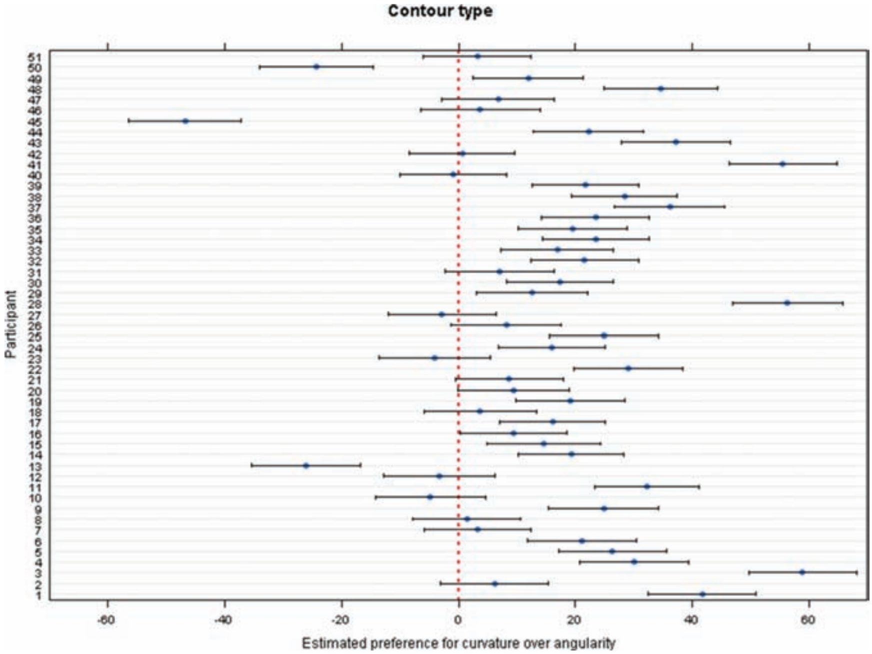

Figure 4. Dots represent, for each participant, the estimated preference for curvature over angularity. Horizontal bars are 95% credible intervals. Credible intervals intersecting with 0 (vertical red dashed line) indicate no clear preference.

As can be seen in Fig. 5, most of the participants preferred shapes with six vertices (an effect of simplicity). Only six participants (P1, P3, P28, P41 and P43) exhibit a preference for shapes with 22 vertices. A few participants did not show a clear preference (indicated by the 95% credible intervals crossing with 0). In sum, it seems that the preference for simple shapes is robust and extends to most participants, with just a few exceptions.

3.3.3. Individual Differences: Movement

As we did for contour type and complexity, to study the individual differences of movement, for each participant we extracted estimated random slopes and added the estimated fixed effect both expansion and rotation (estimated fixed effect 0.78 and 0.35, respectively, see Table 2). In this way, negative estimates indicate a preference for static shapes while positive values indicate a preference moving shapes. These estimates are represented by a dot in Fig. 6 (left panel expansion, right panel rotation). The two panels show, for each participant, the 95% credible interval of the estimates; these are represented by a horizontal line. Credible intervals intersecting zero (crossed by the vertical red

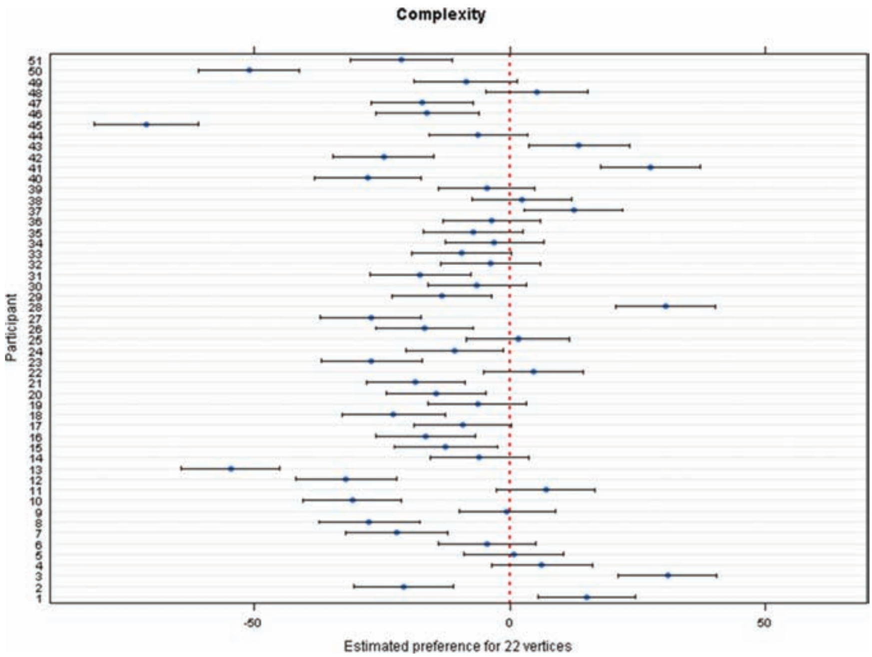

Figure 5. Dots represent, for each participant, the estimated preference for shapes with 22 vertices over shapes with six vertices. Horizontal bars are 95% credible intervals. Credible intervals intersecting with 0 (vertical red dashed line) indicate no clear preference.

dashed line) indicate that for these participants moving or static shapes were practically the same from an aesthetic point of view.

The results of this analysis are shown in Fig. 6. As it can be seen, under our experimental conditions no participant shows any preference for moving or static shapes.

3.3.4. Individual Differences: Interaction between Contour and Complexity

To examine the individual difference in the interaction between Contour type and Complexity, we extracted the estimated random slopes for each participant from the Bayesian model incorporating the estimated fixed effect of their interaction (1.96, see Table 2). Negative estimates indicate a preference for curved shapes when they have six vertices or for angular shapes when they have 22 vertices; positive estimates indicate a preference for curved shapes when they have 22 vertices or for angular shapes when they have six vertices (Note 3). As a result, positive and negative estimates indicate differences in interaction patterns at the individual level. Thus, the sign of the estimates reflects the variation in interaction patterns at the individual level. Figure 7 depicts these interaction estimates as dots, with horizontal lines representing

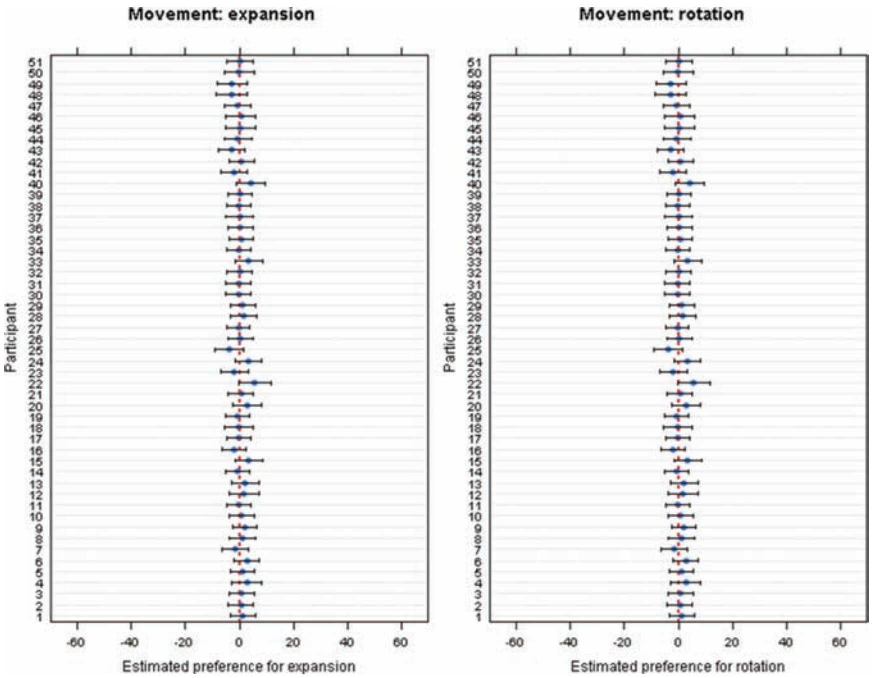

Figure 6. Dots represent, for each participant, the estimated preference for moving shapes over static shapes. Left panel shows the estimated results for expansion, right panel shows the estimated results for rotation. Horizontal bars are 95% credible intervals. Credible intervals intersecting with 0 (vertical red dashed line) indicate no clear preference.

the 95% credible intervals. Intervals intersecting with zero (crossed by the vertical red dashed line) indicate no interaction.

The analysis revealed that nine participants exhibited a negative interaction and eight a positive interaction. These results are interesting when compared to the results of the analysis of individual differences for each variable alone and the global results (Fig. 8 — Note 4).

In the case of the individual differences for each variable, only a few participants deviated from the majority (see Figs 5 and 6). However, for the interaction, the number of participants showing a divergent response pattern is relatively high, making it difficult to identify a clear majority.

Moreover, the Bayesian model's prediction of the global interaction between Contour type and Complexity, shown in Fig. 8, does not indicate any interaction at all. This suggests that individual differences may be masking the overall interaction effect.

These findings together suggest that under our conditions, there was greater consensus among participants regarding preferences (i.e., the preferred level

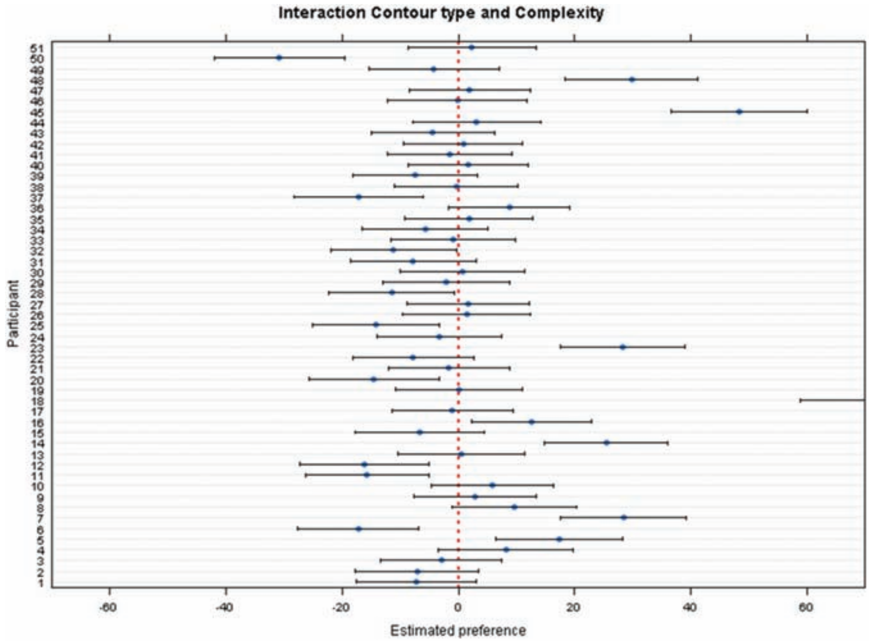

Figure 7. Dots represent, for each participant, the estimated interaction between Contour type and Complexity. Horizontal bars are 95% credible intervals. Credible intervals intersecting with 0 (vertical red dashed line) indicate no clear preference.

within a single variable) than regarding dominance (i.e., the relative strength of a variable). If a specific combination of the Contour type and Complexity was consistently preferred over others, an overall interaction would have emerged, and participants would have shown similar levels of preference and dominance. However, this was not observed.

4. Discussion

In this study, we examined aesthetic evaluations of simple abstract shapes. This experiment involved manipulating three factors: the type of Contour (curved vs angular), Complexity, six vertices vs 22 vertices), and their dynamic attributes (Movement: static, expanding and rotating). Although we manipulated the shape orientation, the results were not discernible and were ultimately collapsed.

From the literature we know that both contour and complexity affect aesthetics. We expected to replicate these effects, and we were especially interested in their interaction. Moreover, we reasoned that if motion added complexity to a stimulus, its effect would be similar to an increase in the

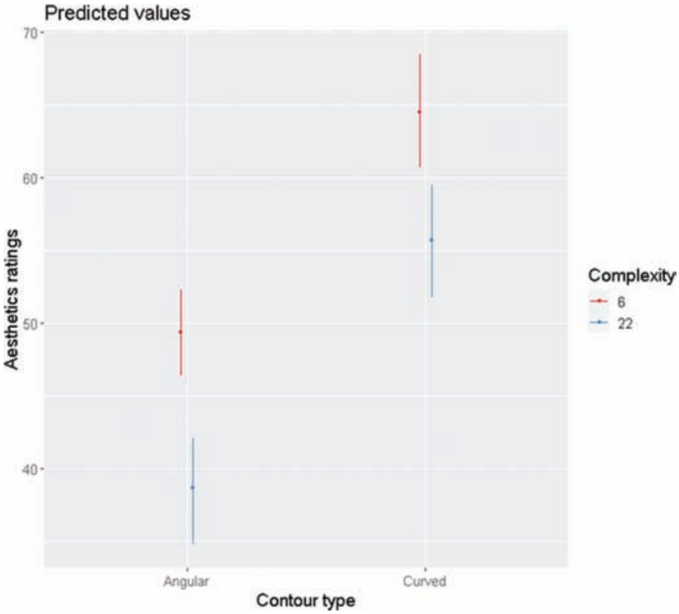

Figure 8. Predicted aesthetics ratings of Contour type and Complexity resulting from the Bayesian model. Dots indicate the predicted means and bars the 89% credible intervals.

number of vertices. Alternatively, if motion affects aesthetics independently of complexity, it should have a differential effect from the number of vertices. Our analysis confirmed that shapes with curved contours are preferred over angular shapes. Quite surprisingly, our results show that simpler shapes are preferred over complex shapes. Furthermore, quite interesting nonsignificant effects emerged. Our results indicated no significant effect of movement and of the interaction between movement and contour.

Nonsignificant findings can prove as insightful as significant ones in some cases. Here, the lack of differences between moving and static shapes supports equivalency between these conditions. This provides evidence that movement does not function as an aesthetic factor for these shapes.

Additionally, psychology has faced criticism over a ‘replication crisis’ and issues like publication bias towards significant effects (Brysbaert, 2019; Makin *et al.*, 2020). Such factors have undermined trust in research findings. As one of the first attempts at analysing interactions between aesthetic variables, our results — both significant and nonsignificant — are valuable. The individual differences patterns also provide useful insights. Overall, fully and transparently reporting diverse types of results guards against overinflated effects and contributes substantive evidence, even if patterns appear counterintuitive or contrast theoretical predictions. The effects emerged in this study are discussed in turn.

4.1. Contour Type

In line with our expectations and previous literature cited in the Introduction, a clear contour effect emerged. The ratings of shapes with curved contours were higher than those of similar shapes with angular contours. In general, when shapes are simple and unfamiliar, curved contours are preferred. The precise cause of this preference is still debated, including factors such as avoidance of angular angles (Bar and Neta, 2006), secondary sexual characteristics (Hübner *et al.*, 2023), and tuning to natural environment properties (Bertamini *et al.*, 2019).

4.2. Complexity

Our results revealed a preference for simplicity, with shapes having six vertices being favoured over those with 22 While this was not anticipated, it aligns with existing literature. Bertamini *et al.* (2015) identified dual effects for abstract shape preferences: one favouring simplicity and the other favouring complexity. In their study, stimuli were generated from three variations of the Cassini oval function — a simple circle, an oval, and a more complex peanut shape — referred to as articulation. The simpler, circular articulation was preferred. However, in that study, when manipulating the number of vertices, a preference for shapes with 26 vertices over those with 22 vertices emerged.

This suggests that the effect of complexity on preference is likely nonmonotonic. Preferences lean towards more circular, round shapes, which could explain our finding, as shapes with only six vertices resemble circles or squares. Yet, as complexity increases, aesthetic appeal may also rise.

Phillips *et al.* (2011) found similar trends with three-dimensional abstract shapes, showing preferences for both simple ‘blobs’ and more complex stimuli at opposite ends of the complexity spectrum. The role of complexity in aesthetics is therefore nuanced. Berlyne (1971) proposed an ideal complexity level described by an inverted U-shape curve, but this does not fully account for our findings or previous results with abstract shapes. Instead, preferences for abstract shapes might follow a U-shaped function concerning complexity. This idea is supported by other research indicating that preferences are influenced by multiple factors, such as symmetry and order (Gómez-Puerto *et al.*, 2015), making it difficult to reduce aesthetic preferences to universal principles.

Our study highlights the nuanced interactions between shape characteristics driving aesthetic responses and significant individual differences. Indeed, our analysis revealed that for some participants, complexity positively influenced aesthetics. Mather *et al.* (2023) also found considerable individual differences in responses to complexity, suggesting that factors such as art exposure might play a critical role in these preferences.

4.3. Movement

Previous studies found effects of movement (see Introduction), but our study did not support the hypothesis that movement, per se, adds significantly to the aesthetic ratings. There was an effect of complexity in terms of number of vertices, and therefore movement did not have an effect similar to that of complexity. If movement was a type of complexity, simple moving shapes should have been rated lower than static shapes. One way to interpret these results is to consider movement as an intrinsic property of objects. For our simple abstract shapes movement was not an intrinsic characteristic of these shapes. Instead, the movement of, for example, a cheetah is a manifestation of its innate elegance and skill. It is likely that a moving cheetah would appear more pleasing than a static cheetah. In this regard, analysing dancing humans' aesthetic preferences, Calvo-Merino *et al.* (2008) found that movements of dancers which include more displacement (such as jumping) were preferred over dances involving relatively small displacement (involving only one limb). Future experiments will clarify whether movement is an aesthetic feature, at least for entities where movement is an intrinsic characteristic, such as cheetahs or dancers.

As mentioned in the Introduction, Soranzo *et al.* (2018) found a robust effect of aesthetics on IOs. These are objects that behave autonomously. To explain this effect, the authors suggested that IOs elicit an arousal effect. IOs improve arousal, which might improve aesthetic experience. The results of our experiment do not support this interpretation. IOs might have been preferred to static objects because of novelty or feedback.

(a) *Novelty interpretation*: Although we are used to objects that exhibit autonomous behaviour when managed, such as smartphones, IOs might have been perceived as novel because we are not familiar with them. (b) *Feedback/Reward interpretation*: IOs exhibit autonomous behaviour in response to participants' actions. IOs become active when picked up and stop when put down. Participants may have liked the fact that IOs 'acknowledged' that they touched them. Therefore, the feedback provided by IOs might be a reward that increased their appeal.

An incremental effect of curved shapes might have been anticipated, with the difference between curved and angular contours for simple shapes being higher than the same difference for complex shapes. However, this was not the case; no interaction emerged between these two variables. This suggests that these variables are independent. However, strong individual differences in aesthetic judgements emerged. Few individual differences emerged in the analysis of each factor separately, and the differences between individuals were more evident in the interaction analysis. As highlighted in the Introduction, when studying multiple aesthetic variables at the same time, it is interesting to analyse not only the preference for specific properties, but also dominance, the relative importance of one variable over others.

Some participants assigned higher aesthetic ratings to smooth-simple and smooth-complex shapes and lower values to angular-simple and angular-complex shapes, indicating that they based their decision on the type of contour of the shapes (their dominant variable was contour type). However, other participants assigned higher aesthetic values to simple-smooth and simple-angular shapes and lower ratings to complex-smooth and complex-angular, indicating that their dominant variable was complexity. Understanding these individual differences has important implications for the interpretation of aesthetic preferences.

As ratings were relatively less consistent with regard to the interaction than with regard to each variable taken in isolation, it seems that there was more variation in dominance than in preference. Further studies will clarify whether this is a general trend characterising interactions of further aesthetics variables. Indeed, this may suggest an explanation for the wide variation in preferences for complex stimuli, such as art. These variations may be better understood by considering the significance attributed to different variables, termed dominance, rather than focusing solely on preferences within each aesthetics variable.

4.4. Limitations and Constraints on Generality

We must stress that our study's findings cannot be generalised to familiar shapes. Also, we used two-dimensional shapes displayed on a computer screen; findings might not generalise to three-dimensional shapes. Instead, we have no reason to believe that the results depend on participants' characteristics (Simons *et al.*, 2017).

5. Conclusions

The findings can be summarised as follows. As in previous studies, our analysis revealed that for abstract shapes curved contours are preferred over angular contours. An effect of simplicity also occurred, which was less predictable. Individual differences, however, emerged, suggesting that some people prefer more complex shapes, although they were a minority in our study. Adding movement to these shapes does not alter their aesthetics; this also indicates that movement does not increase complexity. We finally found that, on average, contour type and complexity do not interact with each other. It was found, however, that significant individual differences emerged when examining this interaction, indicating that people differ primarily in dominance as opposed to preference.

Author Contributions

Conceptualisation, A.S., F.B., M.B.; methodology, A.S.; software, M.B.; validation, F.B.; formal analysis, A.S.; investigation, F.B.; resources, F.B.; data curation, A.S.; writing — original draft preparation, A.S.; writing — review and editing, M.B and F.B.; visualisation, A.S.; supervision, A.S. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

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Institutional Review Board

The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of Sheffield Hallam University (protocol code: ER51349370; 12/04/2023).

Informed Consent

Informed consent was obtained from all subjects involved in the study.

Data Availability

Experiment source code, data, videoclips examples of moving shapes, and R script are available at: https://osf.io/x7mwc/

Notes

1. Unlike confidence intervals that give a single confidence level, Highest Density Intervals provide a range of probabilities for an estimated parameter value. The key distinction is that for HDIs, every value inside the interval has a higher probability of being the true parameter value compared to any value outside the interval bounds.
2. Smaller values provided by the leave-one-out (LOO) information criterion indicate better fit. To determine whether one model is superior to the other, the difference in the LOO information criterion between the two should exceed twice the corresponding standard error.
3. When the magnitude of the preferences for one level over another within a variable is very high, negative and positive estimates could, in principle, emerge with other combinations of the two variables (e.g., a negative estimate could emerge also for curved shapes with six vertices when the magnitude of the preference for smooth contours is very high).
4. This result is similar to the descriptive analysis shown in Fig. 2 with the differences that data are collapsed with regards to movement and are predicted, rather than actual, values.

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