Article

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Beautiful on the inside: Aesthetic preferences and the skeletal complexity of shapes

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Abstract
A plain, blank canvas does not look very beautiful; to make it aesthetically appealing requires adding structure and complexity. But how much structure is best? In other words, what is the relationship between beauty and complexity? It has long been hypothesized that complexity and beauty meet at a "sweet spot," such that the most beautiful images are neither too simple nor too complex. Here, we take a novel experimental approach to this question, using an information-theoretic approach to object representation based on an internal "skeletal" structure. We algorithmically generated a library of two-dimensional polygons and manipulated their complexity by gradually smoothing out their features—essentially decreasing the amount of information in the objects. We then stylized these shapes as "paintings" by rendering them with artistic strokes, and "mounted" them on framed canvases hung in a virtual room. Participants were shown pairs of these mounted shapes (which possessed similar structures but varied in skeletal complexity) and chose which shape looked best by previewing each painting on the canvas. Experiment 1 revealed a "Goldilocks" effect: participants preferred paintings that were neither too simple nor too complex, such that moderately complex shapes were chosen as the most attractive paintings. Experiment 2 isolated the role of complexity per se: when the same shapes were scrambled (such that their structural complexity was undermined, while other visual features were preserved), the Goldilocks effect was dramatically diminished. These findings suggest a quadratic relationship between aesthetics and complexity in ways that go beyond previous measures of each and demonstrate the utility of information-theoretic approaches for exploring high-level aspects of visual experience.

Keywords
shapes/objects, aesthetics, information theory, complexity

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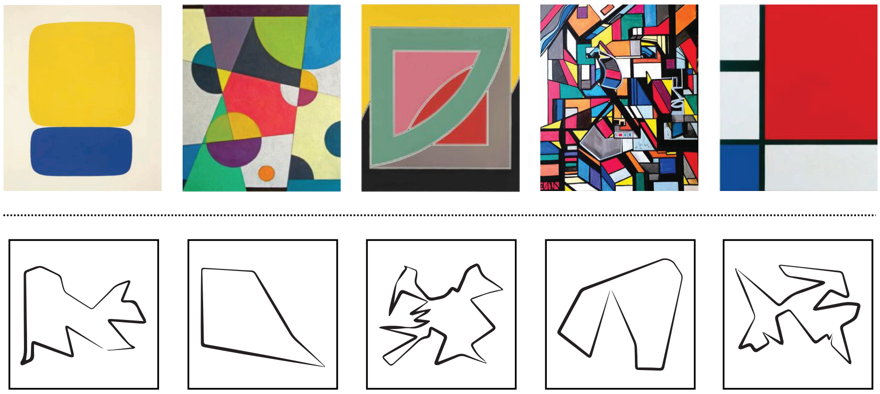

Figure 1. Images differ in their beauty, and also in their complexity. As shown here, impressions of beauty and complexity can arise not only for images that are ornamented or otherwise intended to be beautiful (e.g., the works of art in the top row) but also for much more ordinary images composed of simple contours (e.g., the collections of shapes in the bottom row). Despite the relative sparseness and low dimensionality of these shapes (which were generated algorithmically and are used in the present work), they nevertheless give rise to these dual impressions: some look more or less aesthetically appealing, and some look more or less complex. The present work explores how these two properties interact.

Look at the images in Figure 1. Beyond your experience of the colours, textures, and shapes present in each panel, you may also find yourself with two other impressions: (1) some of these images may seem more or less *beautiful* to you; and (2) some of these images may seem more or less *complex* to you. These two impressions may even interact with one another: Some images may look more or less beautiful *because* they look more or less complex. These impressions thus invite a question: what is the relationship between beauty and complexity?

Complexity and Beauty: A "Sweet Spot"?

One possibility is that simplicity is most beautiful, as in works of art involving idealized forms without much extra ornamentation. Indeed, there is often something quite appealing about viewing even simple geometric shapes, such as the Ensō figure in Zen Buddhism, or even structures such as the Great Pyramid of Giza. Alternatively, another possibility is that more complex and embellished images are seen as most beautiful, as in a frenetic Jackson Pollock canvas or an ornate stained-glass window.

Of course, nearly any image can be interpreted as beautiful in the right context, and appreciating the beauty in an image goes well beyond its purely visual properties. However, it has been long speculated that *holding all other factors constant*, beauty varies with complexity in neither of the above two ways but rather in an inverted-U fashion, such that the most beautiful images are those that are neither too simple nor too complex.

Indeed, a series of studies from the middle of the last century found evidence that aesthetic preferences are greatest for images of "intermediate" complexity (Dorfman & McKenna, 1966; Munsinger et al., 1964; Munsinger & Kessen, 1964; Vitz, 1966; Walker, 1970). In one of these studies, for example, children and adults were shown polygons that varied in their number of sides, from 3 sides up to 40 sides (Munsinger & Kessen, 1964); both older and younger participants preferred shapes with 10 sides over all others. This relationship is also predicted by theoretical accounts of aesthetic experience, such as Berlyne's arousal theory (Berlyne, 1973), where moderate complexity and arousal potential result in maximal preference (for a recent discussion along similar lines, see Van Geert & Wagemans (2020); but see also Brielmann & Pelli (2018)).

Theoretical and Empirical Challenges

Despite the longstanding interest in (and promise of) this hypothesis, it has also faced a number of difficulties.

First, even the most suggestive results have not always been consistent with one another. For example, other studies on aesthetic judgments of shapes have found conflicting patterns relating beauty to complexity, such as a monotonic relationship where more and more complexity is seen as less and less appealing (Day, 1968), or even bimodal distributions (Day, 1967) that are almost opposite the middle-is-best theory. Still other work has speculated that overall U-shaped trends are actually driven by subsets of participants with preferences at either extreme, such that most participants *do not* especially prefer medial complexity but the group only appears to in aggregate (Güçlütürk et al., 2016).

Indeed, these inconsistencies may derive in part from a second difficulty facing this literature: a major challenge in all such studies is how to manipulate visual complexity in the first place. In the studies mentioned above, complexity was varied by a shape's number of sides; but who is to say that number of sides is the relevant measure of complexity? After all, it seems conceivable that two shapes of equal side numbers might vary in visual complexity for other reasons, or even that a shape with fewer sides might be more complex than one with more sides—for example, if the former seems to have more "parts," if the parts are more richly connected to one another, and so on.

This second difficulty is related to a third and final difficulty: How to isolate visual complexity itself from other features that may correlate with it. For example, shapes with more sides tend to require more "ink" to produce (and amount-of-ink has even been used as a measure of complexity; Berlyne, 1958; Vitz, 1966), have a higher spatial frequency, and so on—making it unclear just what property is driving preferences in these tasks (whatever those preferences may be).

In light of these difficulties, recent work on complexity and beauty has developed new methods and approaches to overcome such challenges. However, in order to do so, this newer work has often had to depart from the sorts of stimuli used in the classical studies described above. For example, recent findings have found an inverted-U-shaped relationship between beauty preferences and the entropy (Lakhal et al., 2020) or fractal dimension (Spehar et al., 2003, 2016) of images, in ways that manipulate complexity objectively and in some cases even control for lower-level correlates of these measures (Spehar et al., 2003). However, in order to gain this sort of experimental control, the stimuli have often been somewhat obscure or esoteric—such as unsegmented textures of dots or clouds (Lakhal et al., 2020), or dense patterns of fractal noise or intersecting lines (Spehar et al., 2003)—rather than the sorts of organic-looking objects that have been used in earlier work and that, say, a child might draw (cf. Imamoglu, 2000). Can the rigour of these newer approaches be used to capture the insights and experiences of more classical studies?[1]

A Computational Geometry Approach

Here, we explore such an approach. Recent advances in computational geometry make it possible to quantify the information density of a *shape*, by first extracting a representation of its internal "skeleton" (Figure 2). The shape skeleton is a blueprint-like representation that captures many global and local patterns within a shape, and it can be analysed for its "surprisal" (Feldman & Singh, 2006)—a measure of how predictable or unpredictable one part of the skeleton is given another part. The surprisal of a branch is its deviation from smoothness; more surprising branches are those with a

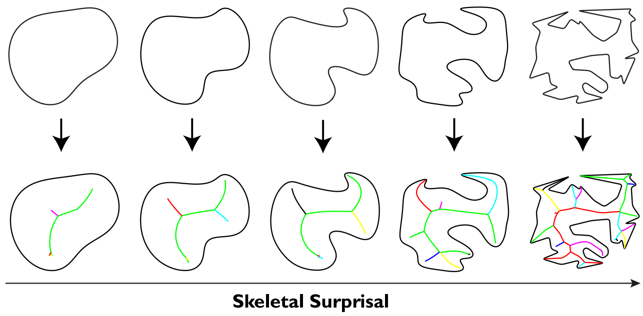

Figure 2. Shape complexity as reflected in the surprisal of the shapes' underlying skeletons. Shown here is a single "family" of shapes from Experiment 1 (upper row), as well as their (increasingly complex) internal skeletons (lower row). (In the actual experiments, these shapes appeared as brush drawings, and without their skeletons; the different colours are used to make the medial-axis branches more distinguishable, but are not significant in any other way.)

greater tendency to zig and zag. Cumulative surprisal is the sum of these zigs and zags, with the addition of a penalty for the number of branches itself. An intuitive way to capture this measure might be to imagine a person walking along the skeleton of a shape; the more often this person changes direction (such that their next step was not easily predictable from their previous step), the higher the surprisal of their walk. This surprisal-based measure just *is* the shape's complexity in a relevant and foundational sense, since it captures how "compressible" the shape is (or, alternatively, how "short" its minimal description is), in ways that can come apart from other shape properties. Moreover, mounting evidence suggests that shape skeletons are psychologically real: They can guide actions directed at shapes (Ayzenberg et al., 2019; Firestone & Scholl, 2014), drive judgments of similarity (Lowet et al., 2018), engage visual attention (Sun & Firestone, 2021), and even play a role in higher-level representations such as category membership (Wilder et al., 2011) and linguistic description (Sun & Firestone, 2022). However, they have not, to our knowledge, been implicated in aesthetic experience itself in any experimental context (though there have sometimes been intriguing suggestions along these lines; Van Tonder et al., 2002).

The Present Studies: Skeletal Complexity in Aesthetic Experience

Here, we take advantage of this approach to explore the link between complexity and beauty in a novel way. We created a library of "families" of geometric shapes; for each shape family, we evolved a series of similar-looking shapes whose complexity smoothly varied from very simple (e.g., a fairly nondescript blob) to very complex (a highly crenulate object with an intricate internal structure; Figure 2). Instead of making aesthetic choices among random polygons that do not share features or body plans, participants could now compare stimuli that originate from the same underlying "blueprint," allowing us to manipulate complexity itself and ensuring that aesthetic judgments primarily reflect this property.

To acquire beauty judgments, we also augment previous measures by designing our experiments to be more immersive. After generating the shape stimuli, we stylize them as "abstract paintings," which then appear to participants on a canvas framed and hung in a room. Unlike previous tasks asking people to assign a beauty rating to a shape without any further context, our approach asks participants to think of their task as selecting the most beautiful painting to hang, creating a naturalistic and engaging context for participants to make their judgments in a more aesthetically appropriate mood.

Finally, we also rule out certain low-level confounds that have been present in previous investigations of beauty and complexity, by running a control experiment in which the same shapes that had appeared previously are scrambled in ways that preserve many of their low-level features but destroy the impression of them as bounded (and beautiful) objects. We ask whether this manipulation weakens or alters the relationship between complexity and beauty.

Together, these experiments explore a longstanding question about aesthetic experience using newer tools and approaches that allow us to go beyond previous findings linking complexity and aesthetic experience.

Experiment 1: A "Goldilocks" Relationship Between Complexity and Beauty

Is visual complexity related to aesthetics by an inverted-U-shaped relationship? In other words, holding other factors constant, do people perceive medially complex stimuli as being more beautiful than stimuli that are "too simple" or "too complex"? Experiment 1 investigated this question for simple and complex shapes.

Method

Open Science Practices. An archive of the data, experiment code, stimuli, and other relevant materials is available at https://osf.io/vzxdy/. For each experiment, we pre-registered the sample size, experimental design, and analyses (including exclusion criteria and some secondary analyses).

Participants. As stated in our pre-registration, we recruited 200 participants for this experiment (mean age = 35 years; 109 female participants and 91 male participants). We chose this sample size based on a smaller pilot study ($N = 30$) that yielded similar results, and conservatively increased the sample size given the ease of online data collection. More generally, larger sample sizes are especially preferable in the domain of aesthetics, where there may be large individual variability in preferences (Palmer et al., 2013). All participants were recruited online via Prolific (https://www.prolific.co/). For a discussion of this participant pool's reliability, see Peer et al. (2017).

Stimuli. All stimuli used here were simple geometric shapes. Shapes have a long history as stimuli in studies of perceived complexity—including studies connecting complexity and beauty (Attneave, 1957; Birkhoff, 1933; Day, 1967; Munsinger et al., 1964)—and they are appropriate here too for several reasons. First, it is surprisingly easy for ordinary geometric shapes to evoke rich (and variable) impressions of both complexity and beauty; indeed, it is striking just how strongly one can feel about the aesthetic qualities of a few connected lines (as you may experience in Figure 1). Second, as noted earlier, advances in computational geometry allow for a succinct and standardized measure of a shape's "objective" complexity based on its internal skeletal structure, such that the complexity of a shape is manipulated systematically (Feldman & Singh, 2006) (Figure 2). Third, such shapes tend to have few (if any) pre-existing associations, ruling out at least some confounding factors that might otherwise contribute to impressions of beauty; whereas an image of a face or a scene might evoke memories or symbolic meanings (which may vary across individuals), ordinary geometric shapes are among the least semantically meaningful stimuli that give rise to impressions of beauty.

To create the stimuli, we algorithmically generated a variety of random-looking shapes, and then "evolved" each of these shapes into a "family" of shapes spanning a wide spectrum of complexity. To first create each shape family's "parent" shape (which was the most complex shape in the family), our procedure defined that the shape would ultimately have 49 sides and then generated

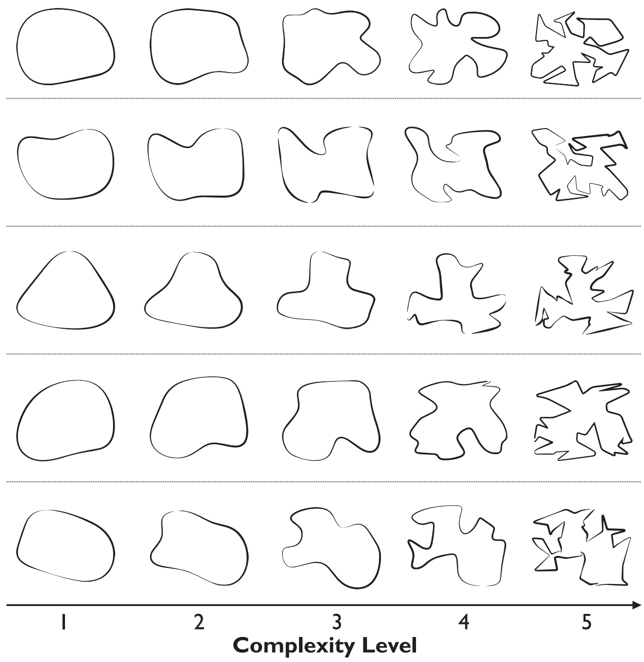

Figure 3. Sample stimuli used in the present experiments. Each row is a distinct "family" of five shapes, which share an underlying skeletal blueprint. Each column is a different level of complexity within a family, with skeletal complexity increasing linearly from Level 1 to Level 5.

a set of randomly located points that should serve as the vertices of the shape's edges. We then connected these points using the method of Delaunay Triangulation, which maximizes the minimum angles formed by the overall structure of the connected lines and thus tends to avoid extremely sharp angles. Next, facets along the boundary of this triangle mesh were removed until the resulting polygon had the predefined number of sides. Finally, for each shape, the edges of the resulting polygon were re-sampled to 1000 points and smoothed in order to appear more natural. Additional constraints included a minimum angle no smaller than 10° and a maximum angle no greater than 170°, such that the turns a shape contain would be discernible.

Next, we derived a shape "family" by gradually simplifying each of the 30 parent shapes (using ShapeToolBox1.0; Feldman & Singh, 2006). A box mask was applied to an increasing number of consecutive points on the contour of the parent shape, such that the curve defined by the points in the mask was flattened to the averaged value along each axis. We started by setting up the mask size as 3 arbitrary units, and then smoothed the shape with that mask to create the next shape; then, we increased the size of the mask by 2 units to create the next shape, by another 2 units to create the next shape, and so on, to eventually create 5 shapes per family, for a total of 150 shapes in the stimulus set. A sample of these shapes can be found in Figure 3.

Overall, the mean normalized skeletal complexity increases linearly with each of the 5 levels, ranging from 0.085 (Level 1) to 0.8 (Level 5), and a one-way analysis of variance (ANOVA) confirmed that our manipulation of skeletal complexity across levels was successful ($F(4, 116) = 1174.60$, $p < 10^{-5}$, $\eta^2 = 0.97$).

Task: Hang a Painting. To probe aesthetic impressions of these stimuli, we introduced a new task in which the participant is asked to select the best "painting" to hang in a room. To best cue the shapes'

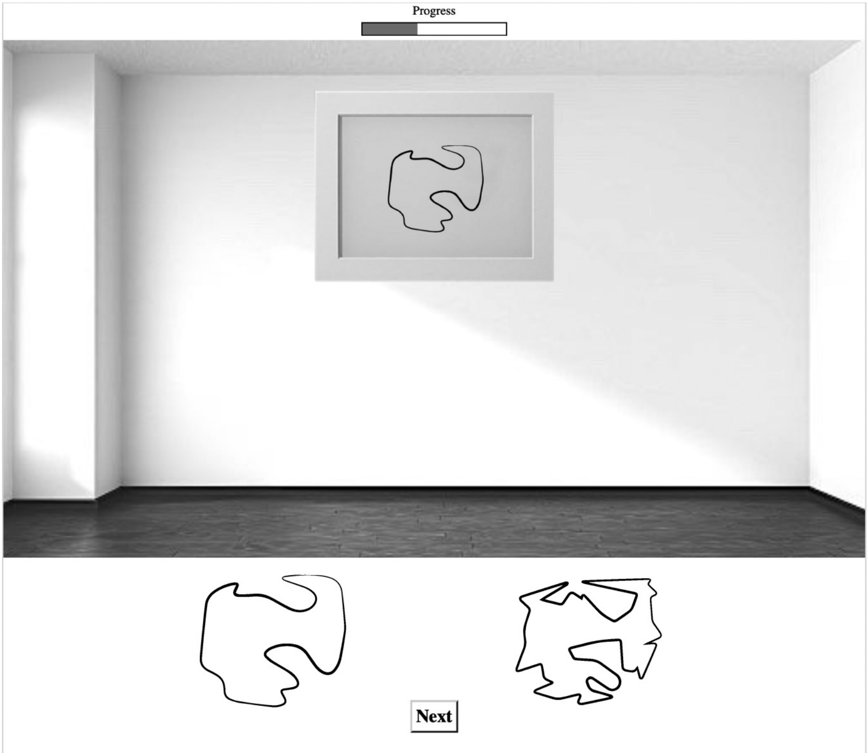

Figure 4. A sample trial of our "*hang a painting*" task, as it appeared to participants in Experiment 1. The trial starts with an empty canvas hung on a wall, and participants may preview how two candidate objects look in a room by clicking on each of them. The participant advances to the next trial by deciding which canvas looks best. Readers can experience this task as participants did at https://www.perceptionresearch.org/beautifulshapes/.

status as aesthetic objects, we stylized our shape stimuli as brush drawings and displayed them to participants as mounted on a canvas in one of 15 possible "frames" which varied in shape and size. These framed shapes then appeared on the "wall" of a fairly non-descript gallery room that might ordinarily display art of this sort.

On a given trial, participants saw two shapes from the same family, and could click each one to have it appear on the wall; their task was then just to indicate which shape-painting looked best. Note that two-alternative forced-choice tasks (2AFC) of this sort have often been thought to be best-suited for aesthetic judgments (e.g., over rating or ranking tasks; Palmer et al., 2013; see also Berlyne, 1958; Munsinger et al., 1964; Spehar et al., 2016), especially when it is possible to exhaust all the relevant pairwise comparisons. The probability of each stimulus being chosen is then taken as the measure of its relative preference (Figure 4).

Results and Discussion

In accordance with our pre-registered exclusion criteria, 7 participants were excluded for failing to provide a complete dataset, leaving 193 participants with analysable data.

As can be seen in Figure 5, the average preference across the five complexity levels showed an inverted-U-shaped pattern: the relative preference peaked at middle levels of complexity, such that participants preferred moderately complex paintings over paintings that were too simple or too complex.

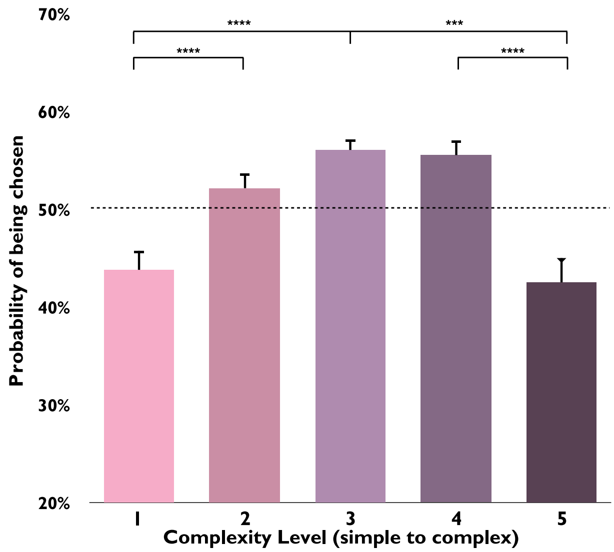

Figure 5. Results of Experiment 1. We observed an inverted-U-shaped relationship between the complexity level of objects and their probability of being chosen. The relative preference first increases with skeletal complexity; however, after reaching a peak, the addition of visual features results in lesser attractiveness of objects. Error bars depict ±1 SEM of the probability of being chosen. Another version of this figure, with individual data points shown, is available in the Supplemental Material.

To better understand these preferences, we ran several pre-registered analyses. First, we grouped the spectrum of shapes into simple shapes (Level 1), moderately complex shapes (Levels 2–4), and overly complex shapes (Level 5), and ran paired *t*-tests between these categories. We found that participants chose moderately complex shapes (54.6%) significantly more frequently than both simple shapes (43.8%; $t(192) = 4.97$, $p = 1.45 \times 10^{-6}$, $d = .36$) and overly complex shapes (42.5%; $t(192) = 4.09$, $p = 6.32 \times 10^{-5}$, $d = .29$).

This simple pattern was also confirmed by the second sort of analysis. First, a mixed-effects model with participant as a random effect revealed a significant quadratic term for the relationship between complexity level and chosen probability ($b = -1.75$, 95%CI[-2.21, -1.29], $t = -7.47$, $p < 2.59 \times 10^{-12}$). Second, a one-way repeated-measures ANOVA revealed a significant effect of complexity level ($F(4, 768) = 10.12$, $p = 1.68 \times 10^{-4}$, $\eta^2 = 0.054$), and subsequent Bonferroni-corrected paired-samples *t*-tests revealed a series of significant pairwise differences (including L1 vs. L2, L1 vs. L3, L1 vs. L4, L3 vs. L5 and L4 vs. L5; all $ts[192] \geq 3.45$, $ps \leq 0.001$, $ds \geq 0.25$; 95% CIs [0.056, 0.11], [0.077,0.17], [0.050, 0.18], [0.070, 0.20], and [0.088, 0.17], respectively).

These results provide evidence for the “Goldilocks” relationship between complexity and aesthetic judgments: The most aesthetically appealing shapes are neither too simple nor too complex, but rather “just right.”[2]

Experiment 2: Shape Complexity *per se*

Experiment 1 revealed that moderately complex objects were preferred over very simple objects and very complex objects, using an approach that allowed us to quantify complexity computationally and acquire aesthetic judgments in a novel aesthetically realistic context.

However, even though our approach aimed to vary complexity itself, the complexity of a shape inevitably correlates with other visual properties. For example, the complex shapes we used—like in previous research (Attneave, 1957; Birkhoff, 1933; Day, 1967; Munsinger et al., 1964)—tend to require more "ink" to draw, have a higher spatial frequency, and so on. Is the Goldilocks effect observed in the previous experiment merely driven by such low-level properties, rather than by more sophisticated representations of complexity itself?

Of course, lower-level features must play *some* role in computations of higher-level complexity (Halberda, 2019); nevertheless, it might be possible to disentangle those influences here. Thus, to rule out a certain form of "low-level" influence in the previous results, we conducted a control experiment to further separate objects' skeletal complexity from more basic visual features. Specifically, Experiment 2 "box-scrambled" the images from Experiment 1. This technique selects random square patches of the image and randomizes their positions, such that many local image features are preserved but the percept of a coherent visual object is eliminated. We then repeated our experiment with these box-scrambled images, which still varied in properties like the amount of ink—and even seemed differently complex, to a degree—but did not give rise to the particular impression of skeletal complexity that we were interested in here. We then asked whether the same pattern would emerge in this context.

In Experiment 2, half of the participants completed the same task (with the same intact stimuli) as in Experiment 1, whereas another half of the participants completed the same task with the box-scrambled stimuli. If the perception of skeletal complexity per se underlies the aesthetic judgments we explore here, then we should observe an attenuated pattern for the box-scrambled images relative to the intact images.

Methods

Participants. Based on a pilot study, we pre-registered a sample size of 500 participants for this experiment, after exclusions—specifically, 250 participants for the *Intact* group and 250 participants for the *Scrambled* group. The mean age of all participants was 37 years, with 254 female participants and 244 male participants (2 participants did not give their gender).

Stimuli and Procedure. To create the box-scrambled images, we divided each intact-shape image (original size: $540px \times 540px$) into a 6×6 region of "boxes" $90px \times 90px$, centred on the objects of interest. We then scrambled the location of the boxes in each image (see examples in Figure 6). Other than

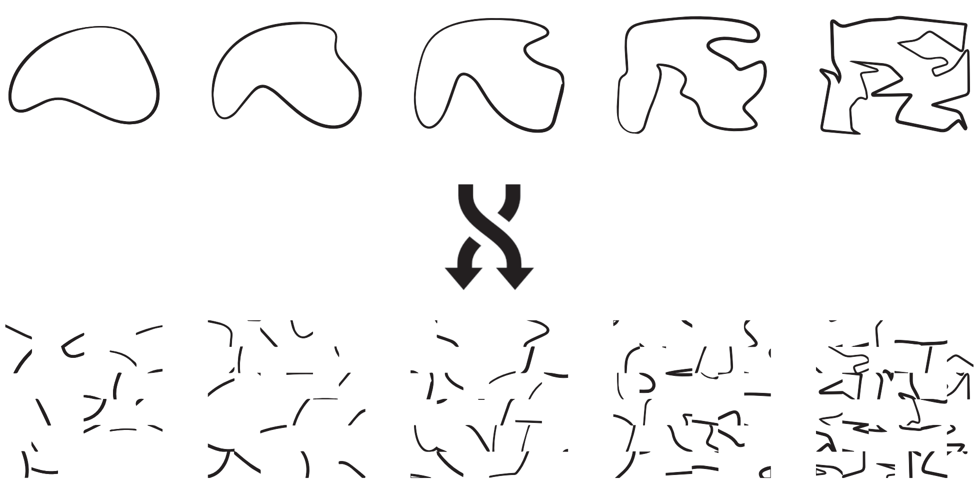

Figure 6. Example stimuli used in Experiment 2. The original objects were scrambled with a 6×6 grid. In this way, the skeletal structure of objects is destroyed, but many of their low-level features remain.

that the procedure was the same as in Experiment 1, with half of the participants in the *Intact* group and half of the participants in the *Scrambled* group.

Results and Discussion

In order to obtain our target sample of 500 participants after exclusion, 530 participants were required in total (of whom 30 were excluded from further analysis for failing to submit complete data).

Intriguingly, the inverted-U-shaped relationship between complexity and aesthetic preference arose in both the *Intact* and *Scrambled* groups, indicating that even the complexity of lower-level features interacts with impressions of beauty. However, this pattern was much more pronounced in the *Intact* group, suggesting that higher-level notions of complexity play a role over-and-above their lower-level correlates.

One way to see this is shown in Figure 7, which plots the preference for moderately complex stimuli (as opposed to the simplest and most complex stimuli) for each condition. As can be seen, moderately complex stimuli were chosen much more often in the *Intact* group than in the *Scrambled* group (with the difference in moderate vs. non-moderate being 11.4% for the *Intact* group vs. 2.9% for the *Scrambled group*, $t(498) = 5.18$, $p = 3.24 \times 10^{-7}$, $d = .46$).

This simple, exploratory analysis was also confirmed by our more detailed, pre-registered analyses. As predicted, a 2 (Scrambled group vs. Intact group) × 5 (Complexity level) mixed ANOVA revealed a main effect of complexity level ($F(3, 1992) = 12.98, p = 1.75 \times 10^{-5}, \eta^2 = 0.025$); and more importantly, there was a significant interaction between group and complexity ($F(4, 1992) = 5.03, p = 0.011, \eta^2 = 0.01$), suggesting that beauty relates to complexity differently in the *Intact* group than in the *Scrambled* group.

In addition to the between-group analysis, we separately fit the data of each group to a mixed-effects model, confirming a robust relationship between beauty and complexity in the

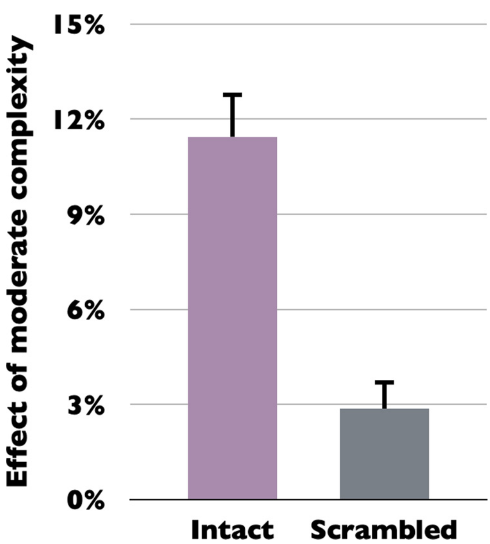

Figure 7. Results from Experiment 2. Even though both the *Intact* and *Scrambled* groups preferred moderately complex images over extremely simple or extremely complex images, this effect was much stronger in the *Intact* group. Error bars depict ±1 SEM. Another version of this figure, with individual data points and trendlines shown, is available in the Supplemental material.

Intact group ($F(2, 248) = 33.12$, $p = 1.78 \times 10^{-13}$), with a significant quadratic term for complexity ($b = -1.97$, 95%CI[− 2.45, − 1.49], $t = -8.05$, $p = 3.07 \times 10^{-14}$). We also discovered a subtle but significant Goldilocks effect in those who viewed scrambled objects, but this effect was significantly attenuated (mixed-effects model: $F(2, 248) = 7.42$, $p = 7.40 \times 10^{-4}$; quadratic term: $b = -0.53$, 95%CI[− 0.84, − 0.22], $t = -3.32$, $p = 0.001$).

Although both groups showed a Goldilocks relationship between complexity level and beauty preferences, this quadratic pattern in scrambled objects was significantly diminished in comparison to intact objects. As can be seen in Figure 6, the scrambling procedure disrupts the images' status as coherent wholes, leaving only lower-level to complexity (e.g. the amount of ink) still remained. These findings thus replicated the pattern from Experiment 1, but also show that higher-level notions of complexity play their own role in the beauty/complexity relationship.

Of course, it is not possible to control for *all* lower-level factors that correlate with complexity, and so other variables may well play a role in generating these results. For example, one such variable is how curved or angular an object is, which is known to influence preference (Bar & Neta, 2006). However, we note that this variable is thought to be *linearly* correlated with preference—curved objects are most typically preferred to angular objects across the board, with more curvature being better (see also Carbon, 2010, 2011). In a more recent study using star-like polygons to manipulate both complexity and curvature, observers showed a stronger preference for simple polygons when they are curved and—more surprisingly—lower preference for moderately complex polygons when they are angular (Palumbo & Bertamini, 2016). By contrast, our work shows a quadratic relationship between visual preference and our variable of interest (complexity). In that case, even if curvature accounts for some portion of the variance in our results, it seemingly would not account for the key quadratic relationship we observe and focus on here.

General Discussion

How does beauty relate to complexity? The present work explored this relationship using one of the most basic kinds of stimulus in vision research: ordinary geometric shapes. Harnessing a new approach to computing the visual complexity of shapes, the results reported here demonstrate that moderate object complexity gives rise to the strongest impression of beauty, whereas overly simple and overly complex objects are seen as less beautiful. Importantly, this "Goldilocks" effect was weakened by scrambling the shapes in ways that preserved many of their low-level visual features but eliminated their higher-level skeletal structure, suggesting that skeletal entropy plays a role in grounding impressions of beauty.

Beauty and Complexity: Where Old Meets New

This work not only provides further evidence for the long-standing "Goldilocks" hypothesis relating to complexity and beauty, but also complements existing empirical work on this topic by combining the precision of newer computationally oriented approaches (which have harnessed new measures of entropy and information density, though often to abstract and sometimes obscure visual patterns; e.g., Lakhal et al., 2020; Spehar et al., 2003, 2016) with the aesthetic sense of classical studies (which have explored more foundational units of visual cognition, but often without the rigour of more modern approaches; e.g., Birkhoff, 1933; Berlyne, 1973; Day, 1967; Munsinger & Kessen, 1964). Our approach characterizes the complexity of an object in terms of its underlying entropy, and specifically in terms of the "surprisal" inherent in its skeleton. To our knowledge, the present work is the first to connect an object's underlying skeletal structure to the perception of beauty, in ways that add to the growing list of cognitive processes where shape skeletons might play a role; Ayzenberg & Lourenco, 2019; Firestone & Scholl, 2014; Firestone & Keil, 2016; Lowet et al., 2018; Wilder et al., 2016; Sun & Firestone, 2021, 2022).

Of course, beauty is a ubiquitous and multifaceted experience that goes far beyond abstract shapes and their skeletons. Appreciating beauty often involves not only basic visual processing but also higher-level cognition, as when we apprehend the underlying messages of an artistic work or its social and cultural significance. For example, one's knowledge of the philosophy expressed by the Ensō figure may be relevant to experiencing the beauty inherent in its simplicity. Additionally, there is a component of aesthetic visual experience that is shaped by one's prior history with a stimulus class, as in ecological valence theories of preference (Palmer & Schloss, 2010), as well as a complex interplay between the emotions that a stimulus evokes and our subsequent impression of its appearance (Madan et al., 2018). However, beyond these factors, there is surely *also* a component of aesthetic experience that derives from more basic aspects of visual processing, and our work joins the many studies that have explored those more basic factors, such as orientation (Latto & Russell-Duff, 2002), curvedness (Bar & Neta, 2006), symmetry (Damiano et al., 2021), and more (Birkhoff, 1933; Chen et al., 2021; Graham & Redies, 2010; Lakhal et al., 2020; Milne & Herff, 2020; Palmer et al., 2008; Palmer & Guidi, 2011; Vitz, 1966).

Studying Beauty, Beautifully

Another contribution of the present work is our method of acquiring judgments of beauty. Though images can be aesthetically pleasing even without any special engagement with them, it stands to reason that aesthetic experiences are most natural when they arise in contexts that actively promote aesthetic engagement. Whereas much previous psychological work on aesthetic experience (perhaps even the vast majority of such work) collects beauty judgments by asking for numerical ratings of images, our approach was to ask participants to consider our images as though they were "paintings" hung in a gallery, and to select which painting would best decorate the room.[3] By adding a beauty-related scene and preview function to a commonly used 2AFC task, we provided participants with an appropriate and familiar context in which to make aesthetic judgments (here, decorating a room).

Though it might be challenging to reproduce a fully immersive aesthetic experience in a laboratory setting, there may be value in studying the perception of beauty in a way that itself feels "beautiful."

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Supplemental Material

Supplemental material for this article is available online.

Notes

1. Whereas our discussion here focuses on work using basic and abstract visual stimuli, another line of research explores the relationship between complexity and beauty in much richer visual images, such as natural scenes and visual arrays composed of many elements. Recent work on computational measures to quantify visual complexity over such stimuli, in terms of properties such as the degree of visual clutter in an image (Rosenholtz et al., 2007), the size of the digital file in which the image is stored (e.g., JPEG and GIF file size in Marin & Leder, 2013), its self-similarity (Spehar et al., 2016), or the combination of these and other aspects (Fernandez-Lozano et al., 2019). However, these summary approaches, while very valuable and effective in the broader domain of image-level properties, seem less suited to visual *objects* themselves, a basic processing unit defined by its boundedness, cohesion, part-based structure, and so on. The rest of our paper thus focuses more on measures suited to object-level complexity rather than image-level complexity.
2. Güçlütürk et al. (2016) suggest that inverted-U relationships between complexity and liking could result from the combination of two distinct groups. For example, perhaps one subgroup of participants finds simple stimuli aversive, but is positively disposed to moderately and highly complex stimuli, while another group finds complex stimuli aversive but is positively disposed to moderate and simple stimuli. We examined our data and ruled out this result as well. Among 193 participants, only 34 people were most frequent in choosing the simplest objects, and 61 preferred the most complex objects; a strong majority of participants preferred moderately complex objects.
3. One limitation of the current study is that we mounted the stimuli on a fixed background (a gallery room), partly because this context seemed appropriate for the abstract "paintings" we used as stimuli. However, this naturally raises a question about the role of such contextual factors in participants' choices. Future work using this task could vary the context in which these images appear, to ask whether very different environments alter the relationship between complexity and beauty.

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