Complexity is a unified cognitive kind

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Abstract

Any information-processing system must deal with the complexity of its input. Yet, complexity arises in many forms: An image may be complex, a melody may be complex, and so too for linguistic or mathematical expressions. Are these disparate forms of complexity 'unified' in the mind, such that cognition represents a common quantity shared across qualitatively different types of information? Here, 11 experiments (*N*=1500) reveal domain-general representation of complexity. First, a reward-transfer task revealed that outcomes associated with complexity generalize across diverse stimulus classes, including shapes, dot-arrays, melodies, letter-strings, mathematical expressions, and tactile forms. Subsequent experiments demonstrated that such transfer occurs automatically (intruding on task-irrelevant judgments) and underwrites individual differences in higher-level judgments across domains; for example, participants who find simple shapes aesthetically pleasing also find simple melodies pleasing. These results implicate a capacity for type-independent representation of information density, consistent with a shared representational language across cognitive domains.

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Main text

Intelligent systems must grapple with the complexity of the information they process. In humans, non-human animals, and information-processing machines more generally, meeting this challenge requires efficiently representing complex inputs, often in the service of perception, action, learning, and other downstream processes. This demand is so fundamental that it is often placed at the center of evolutionary accounts of cognition, with some theorists proposing that "the function of cognition is to enable the agent to deal with environmental complexity" (Godfrey-Smith, 1998; Godfrey-Smith, 2013).

Complexity poses a representational challenge not only because complex stimuli contain large amounts of information, but also because different stimuli may be complex for different reasons. A geometric shape, a sequence of tones, or a linguistic or mathematical expression can each be complex — but different features determine the complexity of these very different stimuli. For example, the complexity of a shape may be defined by its number of turns (Attneave, 1957), whereas the complexity of a sequence of tones may be defined by the variety of its rhythm (Bouwer et al., 2018). Are these disparate instances cognitively unified in any meaningful way? Or do they reflect entirely separate notions of complexity that just happen to share the same name?

One clue that seemingly distant cases of complexity in fact share a common currency comes from computer science and information theory, where the discovery of 'universal compression algorithms' demonstrated that complex information of any type or format can be compressed by the same procedure (see also Kolmogorov, 1965; Solomonoff, 1964; Hutter, 2005). Such algorithms compress data without regard for the data's type or source distribution, facilitating efficient storage and recovery (as in ZIP compression; see Lempel & Ziv, 1976; Ziv & Lempel, 1978; Welch, 1984). The significance of this demonstration arises not just from its efficiency, but also from its universality, applying to text, visual images, auditory sequences, or any arbitrary data format (MacKay, 2003; for extended discussion of Kolmogorov invariance, see Li & Vitányi, 2008). This implies that all complex stimuli, no matter their format, share a stimulus-invariant property that is (at least in principle) extractable by information-processing systems.

These observations raise a question for psychology: Does the mind appreciate a universal notion of complexity, abstracted away from any particular domain?

Complexity in the mind: One thing or many?

On the one hand, psychological studies of complexity take a wide range of experimental and theoretical approaches, in ways that seem to implicate a multitude of domain-specific notions of complexity. Considerations of simplicity and complexity underlie many important aspects of cognition (for review, see Chater, 1999; Chater & Vitányi, 2003; Feldman, 2016); but research on cognitive representations of complexity typically focuses on one kind of complexity in isolation (cf. Boger & Keil, 2025). For example, in the realm of visual complexity — the complexity of a visual shape or pattern — previous work reveals that complexity drives memory

(Alvarez & Cavanagh, 2004), attention (Sun & Firestone, 2021), aesthetic preferences (Osborne & Farley, 1970; Sun & Firestone, 2022a), word-labeling (Lewis & Frank, 2016), and even verbal descriptions (Sun & Firestone, 2022b). However, the specific notions of complexity explored in such work do not — and often cannot — interact with each other. The complexity of an image has been defined by its fractal dimension (Spehar et al., 2003); the complexity of a geometric shape has been defined by the structural surprisal of its shape skeleton (Sun & Firestone, 2021); the complexity of a labeled object has been defined by the number of geons it contains (Lewis & Frank, 2016); and so on. Beyond vision, the complexity of a concept has been defined in terms of Boolean compressibility (the length of the shortest logically equivalent propositional formula; Feldman, 2000; Feldman, 2003); the complexity of a tool has been defined in terms of functional diversity (Ahl & Keil, 2017); and the complexity of a social network has been defined in terms of its graph structure (Butts, 2001). (Even within a single domain or stimulus class, 'complexity' may have many different referents or definitions; for example, in considering the complexity of a taste or odor, one might consider the chemical complexity of the molecules, the perceived complexity of the experience they evoke, and so on; Spence & Wang, 2018.) These vastly different approaches to complexity in psychology — both across and within domains — may promote theorizing of complexity as constituting many different domain-specific quantities that only happen to share the same name.

On the other hand, there is an intuitive sense in which we can appreciate aspects of complexity that are shared across very different contexts. Consider Figure 1, which depicts complex and simple stimuli from many domains including images, sounds, and linguistic or mathematical expressions. Despite the variety of those stimuli, it may nevertheless feel that there is a single underlying quantity that unifies them — something that separates the top row from the bottom row even across their different domains and features. This raises the intriguing possibility that complexity is mentally represented in a more domain-general manner.

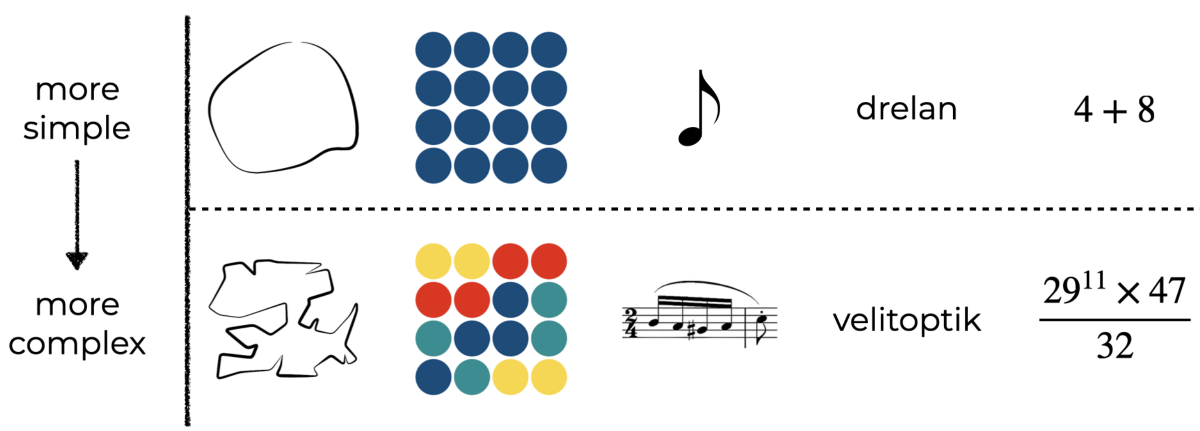

Fig 1. Simple and complex stimuli from diverse domains. The features that give rise to complexity are qualitatively different across domains — for example, the complexity of a geometric shape may be defined in terms of its number of turns, while the complexity of a mathematical expression may be defined in terms of the operations it contains. The present work asks whether the mind extracts and represents a shared property across these domains.

Recent experimental evidence suggests that the mind relies on a compression-like algorithm to represent stimuli within a particular domain. For example, it has been proposed that a 'language of geometry' — wherein geometric patterns are deconstructed into primitive symbols such as line segments and curves recursively composed with operators such as 'turn' and 'move' — forms the basis for mental representations of shapes (Amalric et al., 2017; Sablé-Meyer et al., 2022; Adriano et al., 2025; Revencu et al., 2026; see also Hafri et al., 2023a; Lowet et al., 2018). Such representations rely on faithfully compressing a shape into its minimal form (a capacity that may even reflect a signature of uniquely human reasoning; Sablé-Meyer et al., 2021). Similar kinds of compressed representations may arise in other cognitive domains, such as language, audition, and more (for review, see Dehaene et al., 2022), and they predict performance on a variety of cognitive tasks (see Mathy & Feldman, 2012; Al Roumi et al., 2021). Such proposals also interact with longstanding discussions of the format of mental representations, including the possibility that a more general 'language of thought' pervades the mind and underwrites performance in otherwise-disparate cognitive domains (Fodor, 1975; Quilty-Dunn et al., 2023). This picture of mental organization would naturally enable exactly the sort of cross-domain interaction (for example, between geometry and tones, or language and math) that we explore here.

<u>The present experiments: Complexity transfer across domains</u>

Here, we ask whether the mind represents complexity in a domain-general manner. Our approach is to test whether representations of complexity 'transfer' from one domain to another. In other words, we ask: If some pattern is associated with complexity in one domain, will that same pattern transfer to a completely different domain? This approach allows for the study of many different kinds of complexity at once, in contrast to previous studies that typically examine a single type of complexity in isolation. We conducted 11 experiments that explore this question using three different paradigms. Experiments 1–7 demonstrated that information a participant acquires about complex stimuli in one domain informs their judgments about complex stimuli in other domains, spanning visual, auditory, linguistic, mathematical, and tactile modalities. Such transfer was not explained by merely representing 'more' of any arbitrary stimulus dimension, as transfer did not arise for saturation (Experiment 6a), brightness (Experiment 6b), or size (Experiment 6c). Experiment 8 showed that such transfer occurs automatically, such that incidental exposure to task-irrelevant complex stimuli in one domain intrudes on basic judgments made in another domain. Finally, Experiment 9 revealed stable individual differences in aesthetic judgments of complexity across domains, in ways that seem explicable only by a domain-independent, individual-level preference for information density of a certain degree. Together, these results suggest that the mind possesses a unified representation of complexity abstracted away from the surface features of a given stimulus, opening the door to questions concerning the evolutionary, developmental, and computational foundations of complexity representation.

Results

Experiments 1–7: Reward-transfer across domains

Our first set of experiments (Experiments 1–7) leveraged a reward-transfer task to ask whether outcomes associated with complexity in one domain transfer spontaneously to other domains. We designed a reward-learning task consisting of two parts. In the first part of the task (the learning phase), participants completed 12 trials in which they chose between a simple and complex stimulus from a given domain (for example, a simple geometric shape vs. a complex geometric shape). Participants were consistently rewarded for choosing either the simple or complex option (randomized between-participants), allowing them to associate rewards with either simple or complex stimuli in a given class. Then, in the second part of the task (the transfer phase), participants chose between a simple and complex stimulus of a novel, unseen domain. Participants had never seen this new stimulus class (and thus had never learned a reward-rule to associate with it); they were never instructed about the nature or generality of the reward-rule; and they received only one trial of this novel stimulus class. We asked whether learned associations with complexity generalize to a totally new stimulus class. In other words, having learned to associate greater rewards with choosing complex (or simple) stimuli of one kind (for example, geometric shapes), would participants spontaneously choose complex (or simple) stimuli of another kind (for example, dot-arrays, melodies, letter-strings, mathematical formulas, and so on)?

Experiment 1 tested bidirectional transfer between geometric shapes and dot-arrays (Figure 2A). Though both stimuli are visual, they are complex for seemingly different reasons: A shape's complexity may be determined by (say) its number of turns, whereas a dot-array's complexity may be determined by the number (or arrangement) of its colors. By trial 3 of the learning phase (in which participants received feedback on their selections) performance was 90%; by trial 12 performance was 99%. This suggests that participants successfully learned an implied association between complexity and reward. Our key question, however, concerns the generality of this learned rule; how far does it extend? On the crucial transfer trial, when participants were shown a stimulus pair from the class they had not been exposed to (dot-arrays after seeing geometric shapes, or vice versa), 86.3% of participants selected the reward-earning stimulus ($p < 0.001$ in exact binomial test relative to chance, $N = 95$, 95% CIs = [77.8%, 92.5%]); in other words, they readily selected the more variable dot-array after having learned that more jagged shapes were rewarded (and vice versa). Thus, participants did not merely learn a local reward-rule for a given stimulus class (for example, choosing the shape with more turns, or the dot-array with more colors). Rather, their decision rule transferred across stimulus classes in a manner consistent with a domain-general representation of complexity.

Still, shapes and dot-arrays are both visual images, so it may not be surprising to observe transfer across the two. Subsequent experiments thus generalized this pattern much further, testing a very wide range of stimuli. Experiment 2 found successful bidirectional one-shot transfer between geometric shapes and melodies (at a rate of 71.9%, $p < 0.001$, $N = 96$, 95% CIs = [61.8%, 80.6%]; Figure 2B); Experiment 3 found successful bidirectional one-shot transfer between geometric shapes and letter-strings (at a rate of 78.0%, $p < 0.001$, $N = 91$, 95% CIs = [68.1%, 86.0%]; Figure 2C); and Experiment 4 found successful bidirectional one-shot transfer between geometric shapes and mathematical expressions (at a rate of 64.3%, $p = 0.006$, $N = 98$, 95% CIs = [54.0%, 73.7%]; Figure 2D). In other words, having learned simply that more jagged shapes are worth more points, participants selected longer melodies, words with more syllables, and more elaborate mathematical expressions (and vice versa from these stimuli back to shapes). This is especially striking given that, across this broad range of stimuli, individual stimulus pairs not only arise from different modalities but also span from low-level notions of visual complexity to more high-level notions of cognitive or operational complexity. The features of each of these stimuli vary dramatically in type; and in almost every case, there is no obvious way to map these features across their disparate types. In other words, there is no reason to expect the mind to transfer notions of complexity from one domain (for example, curvature of a geometric shape) to notions of complexity from other, very different domains (for example, number of operators in a mathematical expression). Thus, Experiments 1–4 point towards domain-general, one-shot transfer of complexity in a reward-learning task.

Experiment 5 provided further evidence for this transfer by testing all possible stimulus pairs from Experiments 1–4, simultaneously. Rather than testing bidirectional transfer between geometric shapes and other stimuli (dot-arrays, melodies, letter-strings, and mathematical expressions), Experiment 5 tested bidirectional transfer between all of these stimuli at once. Participants were randomly assigned to receive any of the 5 stimulus classes (used in Experiments 1–4) in the learning phase. Then, the transfer phase consisted of one trial of each of the other 4 held-out stimulus classes (all without feedback). This allowed us to test the limits of this domain-generality, asking whether transfer of complexity would arise from any stimulus class to any other stimulus class. Reflecting the generality of these representations, this experiment revealed broad transfer throughout the stimulus space. First, every stimulus class produced successful transfer; participants who received any of the 5 stimulus classes in the learning phase earned rewards at an above-chance rate in the transfer phase (mean transfer accuracy for participants who learned shapes: 74.3%, $t(111) = 9.56$, $p < 0.001$, $d = 0.90$, 95% CIs = [69.3%, 79.4%]; dot-arrays: 68.6%, $t(81) = 5.84$, $p < 0.001$, $d = 0.65$, 95% CIs = [62.3%, 74.9%]; melodies: 81.0%, $t(80) = 11.35$, $p < 0.001$, $d = 1.26$, 95% CIs = [75.5%, 86.4%]; letter-strings: 65.8%, $t(90) = 4.83$, $p < 0.001$, $d = 0.51$, 95% CIs = [59.3%, 72.4%]; mathematical expressions: 61.0%, $t(92) = 3.62$, $p < 0.001$, $d = 0.38$, 95% CIs = [55.0%, 67.1%]). Next, every stimulus class was the ‘target’ of successful transfer; participants who received a single trial of any of the 4 held-out stimulus classes in the transfer phase earned rewards at an above-chance rate (mean transfer accuracy for shape transfer trials: 78.0%, $p < 0.001$ in exact binomial test, $N = 346$, 95% CIs = [73.3%, 82.3%]; dot-arrays: 73.7%, $p < 0.001$, $N = 376$, 95% CIs = [68.9%, 78.1%]; melodies: 63.8%, $p < 0.001$, $N = 378$, 95% CIs = [58.7%, 68.6%]; letter-strings: 65.5%, $p < 0.001$, $N = 368$, 95% CIs = [60.4%, 70.3%]; mathematical expressions: 70.4%, $p < 0.001$, $N = 365$, 95% CIs = [65.4%, 75.0%]). Finally, 9/10 possible bidirectional learning-transfer pairs showed statistically significant transfer (dot-arrays and mathematical expressions: 64.0%, $p < 0.001$ in exact binomial test, $N = 175$, 95% CIs = [56.4%, 71.1%]; dot-arrays and melodies: 75.5%, $p < 0.001$, $N = 163$, 95% CIs = [68.1%, 81.9%]; dot-arrays and shapes: 82.5%, $p < 0.001$, $N = 194$, 95% CIs = [76.4%, 87.5%]; dot-arrays and letter-strings: 62.2%, $p = 0.002$, $N =$

172, 95% CIs = [54.5%, 69.5%]; mathematical expressions and melodies: 65.3%, $p < 0.001$, N = 173, 95% CIs = [57.5%, 72.4%]; mathematical expressions and shapes: 75.6%, $p < 0.001$, N = 205, 95% CIs = [69.1%, 81.3%]; melodies and shapes: 74.1%, $p < 0.001$, N = 193, 95% CIs = [67.3%, 80.1%]; melodies and letter-strings: 72.1%, $p < 0.001$, N = 172, 95% CIs = [64.8%, 78.7%]; shapes and letter-strings: 71.8%, $p < 0.001$, N = 202, 95% CIs = [65.0%, 77.9%]; only mathematical expressions and letter-strings failed to reach statistical significance, but this pair was still numerically above chance: 56.5%, $p = 0.090$, N = 184, 95% CIs = [49.0%, 63.8%]; Figure 2E). Thus, successful transfer arose from, to, and between stimulus classes, suggesting the mind capitalizes on a domain-general representation of complexity.

Experiments 6a–6c controlled for a possible alternative account concerning raw stimulus magnitude. When two stimuli differ in complexity, they must also differ in the magnitude of at least one stimulus dimension (curves in a shape, notes in a melody, and so on). Thus, perhaps our previous results point to the transfer of merely any stimulus magnitude, and not specifically those implicated in complexity. Note that it is difficult to articulate this reductionist explanation without invoking complexity itself; after all, a shape with 'fewer turns' has 'more smoothness', a word with 'fewer syllables' may have 'more readability', and so on. It is only because having more turns is already determinative of complexity that it is subject to transfer. Still, we designed a set of experiments that dissociated complexity from merely having 'more' of any arbitrary magnitude. Experiment 6a used Experiment 1's design — testing bidirectional transfer between geometric shapes and dot-arrays — but included one key additional transfer trial where participants were presented with two colors of identical hue and lightness, but of differing saturation (one 25% and one 75%). Saturation is an appropriate control because it is a continuous, 'prothetic' dimension (Panek & Stevens, 1966) which can be varied while holding other relevant stimulus features (here, hue and lightness) constant. If the mind merely transfers a notion of 'more' from one stimulus class to another, then participants who are rewarded for choosing the more complex geometric shapes (or dot-arrays) should also choose the more saturated color. However, if transfer from one stimulus class to another is operating over a deeper notion of complexity, then participants should not particularly favor one color over the other (while still succeeding on the other transfer trial, as in Experiment 1). The latter is exactly what we observed: Participants successfully transferred the reward-rule between geometric shapes and dot-arrays (84.4%, $p < 0.001$, N = 96, 95% CIs = [75.5%, 91.0%], replicating the results of Experiment 1), but were indistinguishable from chance in the color transfer trial (48.4%, $p = 0.838$, N = 95, 95% CIs = [38.0%, 58.9%], BF10 = 0.26; Figure 2F). (The difference in accuracy between the two transfer trials — the saturation transfer trial and either the shape or dot-array transfer trial — was itself significant as well; $t(94) = 5.99$, $p < 0.001$, $d = 0.62$, 95% CIs = [23.9%, 47.6%].)

Experiments 6b and 6c extended these controls to additional dimensions: brightness and size. Experiment 6b's transfer trial presented gray squares differing in brightness (one 25% and one 75%) instead of the saturation stimuli used in Experiment 6a, and Experiment 6c presented gray squares differing in size (with one having an area 16 times the other). In both experiments, participants transferred the reward-rule between geometric shapes and dot-arrays (Experiment 6b: 81.8%, $p < 0.001$, N = 99, 95% CIs = [72.8%, 88.9%]; Experiment 6c: 83.5%, $p < 0.001$, N =

97, 95% CIs = [74.6%, 90.3%]); but there was no evidence for transfer from shapes and dot-arrays to brightness (43.4%, $p = 0.228$, $N = 99$, 95% CIs = [33.5%, 53.8%], BF10 = 0.54; difference in transfer trials, $t(98) = 6.18$, $p < 0.001$, $d = 0.62$, 95% CIs = [26.1%, 50.7%]) or size (49.5%, $p = 1.000$, $N = 97$, 95% CIs = [39.2%, 59.8%], BF10 = 0.25; difference in transfer trials, $t(96) = 5.21$, $p < 0.001$, $d = 0.53$, 95% CIs = [21.0%, 47.0%]). This suggests that the transfer we observed relies on complexity itself, and not merely any stimulus dimension one can have 'more' of (given that Experiments 6a–6c revealed no evidence of transfer for saturation, brightness, and size).

Finally, Experiment 7 generalized this pattern to an additional modality: touch. We 3D printed the geometric shapes used in previous experiments (using a Bambu Lab X1C printer) and asked whether transfer would arise between these tactile forms and the visual dot-arrays used earlier. As before, participants completed 12 learning trials of a randomly assigned stimulus class (either tactile forms or visual dot-arrays), and then a single transfer trial of the other class. Importantly, participants had no visual access to the tactile forms; the objects were placed inside a closed box with one hole on each side, such that participants could touch the shapes without looking at them. Still, we found successful bidirectional transfer across these domains (at a rate of 81.8%, $p < 0.001$, $N = 99$, 95% CIs = [72.8%, 88.9%]; Figure 2G). In other words, having learned to choose the complex tactile forms, participants spontaneously selected the complex dot-arrays; thus, the observed transfer even extended across vision and touch.

Together, Experiments 1–7 reveal spontaneous reward-transfer of complexity across the visual, auditory, linguistic, mathematical, and tactile domains.

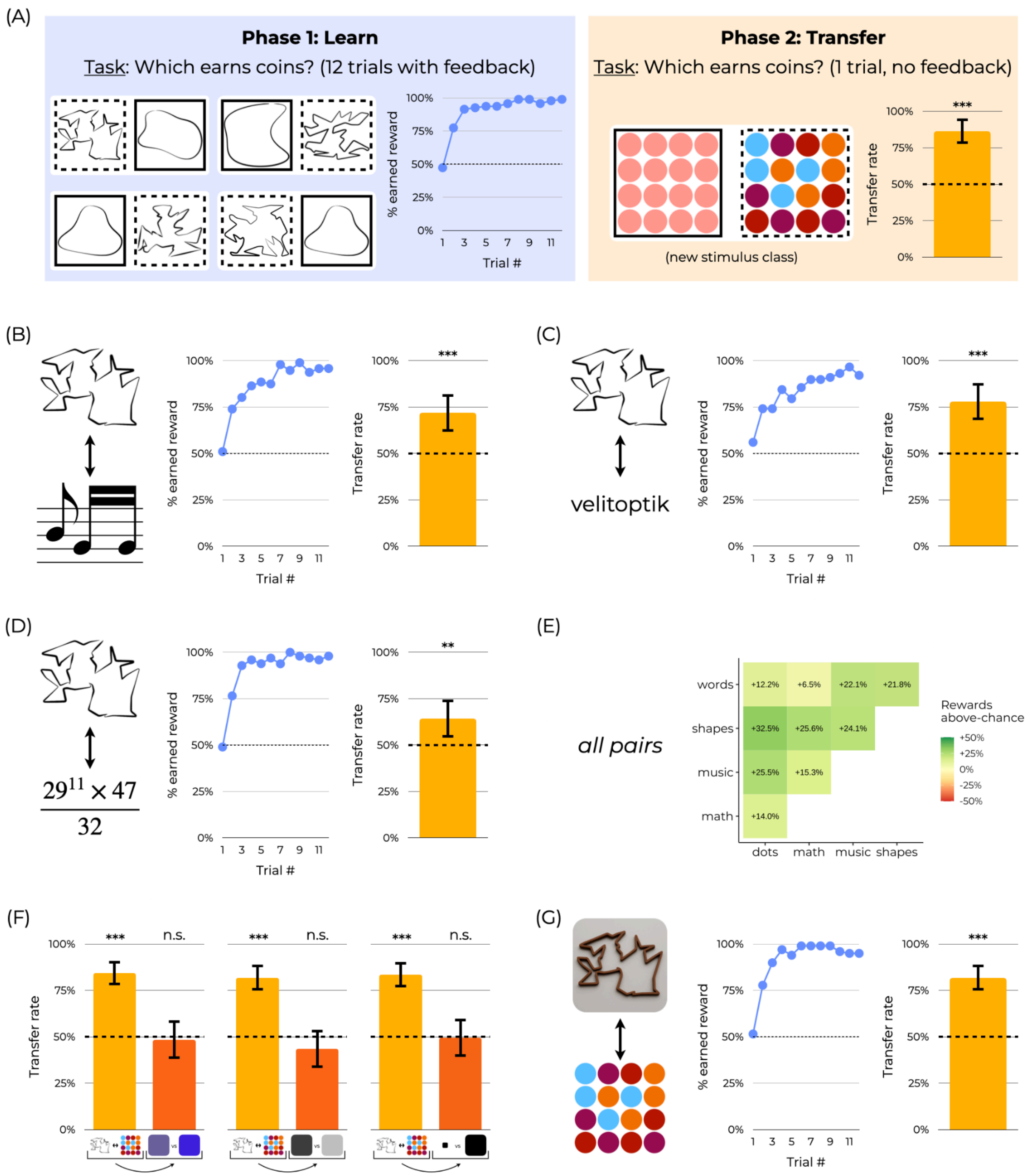

Fig 2. Experimental design and results of the reward-transfer tasks (Experiments 1–7). (A) In each of Experiments 1–7, participants completed 12 learning trials. Each trial contained one simple stimulus and one complex stimulus from a single domain. Participants chose between the two options and received feedback (reward or no reward), allowing them to learn the reward-rule (for example, choosing the complex option earns a reward). Then, participants saw one trial of a new stimulus class which they had never seen before. Experiment 1 (N = 95 post-exclusions) tested bidirectional transfer between geometric shapes and dot-arrays. Participants successfully learned the reward-rule, and then spontaneously transferred it to a previously unseen stimulus class. This suggests that the reward-rule

operated over a general notion of complexity that applied to both classes of stimuli. (B) Experiment 2 (N = 96) tested transfer between geometric shapes and melodies, again revealing successful transfer between the two. (C) Experiment 3 (N = 91) found transfer between geometric shapes and letter-strings. (D) Experiment 4 (N = 98) found transfer between geometric shapes and mathematical expressions. (E) Experiment 5 (N = 459) tested all 5 stimulus classes used in Experiments 1–4 simultaneously. Participants received a random stimulus class in the learning phase; then, in the transfer phase, they received a single trial of each of the other 4 held-out stimulus classes (without feedback). We found successful transfer across domains. (F) Experiments 6a–6c (N = 96, 99, and 97, respectively) ensured that this transfer does not arise for merely any stimulus dimension. These experiments replicated Experiment 1 but included an additional transfer trial where: (a) two colored patches were presented at different levels of saturation, (b) two gray squares were presented at different levels of brightness, and (c) two black squares were presented at different sizes. In each case, we replicated the transfer between the geometric shapes and dot-arrays (found in Experiment 1); but, we found no transfer to saturation, brightness, and size, suggesting that the observed transfer is about complexity per se rather than just more (or less) of any arbitrary stimulus magnitude. (G) Experiment 7 (N = 99) tested transfer between 3D printed tactile forms and dot-arrays. Participants had no visual access to the tactile forms; yet, transfer arose across vision and touch. Readers can view all experiments (with the exception of Experiment 7, which was conducted in-person with tactile forms) at https://perceptionresearch.org/complexity_transfer. Data depicted as mean; when present, error bars represent 95% confidence intervals.

Experiment 8: Automatic interference across domains

Experiments 1–7 revealed that the mind can — and does — transfer complexity across domains. However, the task used in those experiments may seem to actively invite such transfer: It essentially asks participants to make an educated guess about which regularities might apply to the new stimuli they encounter. Could such transfer also be observed in a task where such mapping not only is unnecessary, but also may actively impair performance?

Experiment 8 tested whether complexity transfer arises automatically, such that task-irrelevant complex stimuli in one domain intrude upon judgments about complexity in another domain (see also Sievers et al., 2019). Participants completed a modified Stroop task: On each trial, participants saw two words — one simple word and one complex word — and simply had to say which was more complex. However, above each word appeared a geometric shape that was either congruent to the word's complexity (complex shape above complex word, simple shape above simple word; half of trials) or incongruent to the word's complexity (complex shape above simple word, simple shape above complex word; half of trials; Figure 3A). Since participants only had to judge which word was more complex, they could ignore the shapes entirely (and were explicitly told this). In other words, the shape was (a) completely irrelevant to the word task and (b) demanded no response of any kind. Thus, while participants might infer that complexity was a dimension of interest, nothing about the task required any consideration of shape complexity (indeed, if anything, considering shape complexity would have been actively unhelpful).

Still, shape complexity automatically intruded on judgments of word complexity: Participants gave faster responses on congruent trials (57.4ms difference, $t(47) = 9.07$, $p < 0.001$, $d = 1.31$, 95% CIs = [44.7, 70.1] in paired t-test), and this did not come at the expense of accuracy (indeed, accuracy was higher on congruent trials as well; +2.49%, $t(47) = 3.26$, $p = 0.002$, d = 0.47, 95% CIs = [0.96%, 4.03%]; Figure 3B). Put the other way around, incongruence between shape complexity and word complexity made participants slower and less accurate, impairing their performance. Thus, even though participants could have safely ignored shape complexity and its relation to the stimuli in front of them (and indeed may have performed better if they had done so), they were simply unable to do so; complexity in one domain intruded on judgments of complexity in the other. This suggests that domain-general representations of complexity not only operate on explicit tasks (such as our reward-learning paradigm) but also transfer automatically in ways that interfere with other processes and judgments.

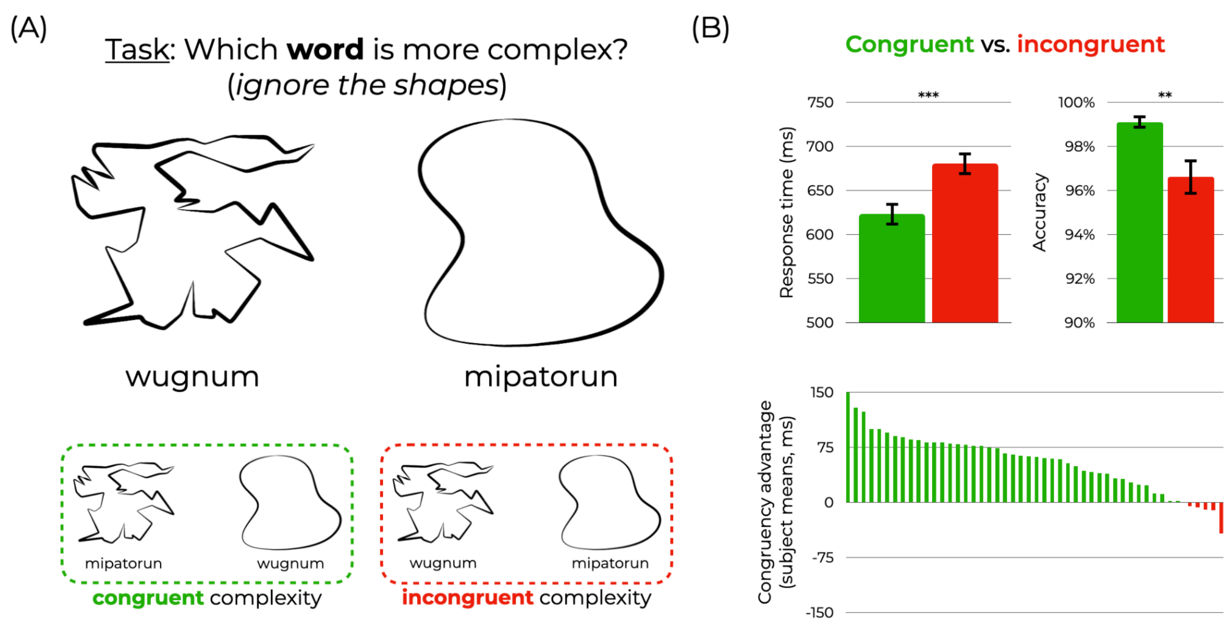

Fig 3. Complexity automatically transfers across domains. (A) Design of the novel Stroop-like task used in Experiment 8 (N = 48 post-exclusions). Participants were presented with two words and had to judge which was more (or less) complex. Above each word, a task-irrelevant shape was presented. Participants were instructed to ignore the shapes, and indeed never had to make any judgments about them — thus, the shapes were entirely task-irrelevant. Importantly, in half of trials, shape complexity was congruent with word complexity (complex shape above complex word, simple shape above simple word); in the other half of trials, shape complexity was incongruent with word complexity (complex shape above simple word, simple shape above complex word). (B) Participants were faster and more accurate on congruent trials than incongruent trials, and almost every participant showed this congruency advantage. This result suggests that task-irrelevant representations of complexity in one domain may automatically interfere with basic judgments of complexity in another domain. Data depicted as mean; when present, error bars represent 95% confidence intervals.

Experiment 9: Complexity preferences are stable across domains

Our previous experiments demonstrate that the mind transfers notions of complexity across domains, in ways that even intrude on basic and incidental judgments. But if complexity is represented as a domain-general quantity, might we find evidence that a single representation governs and unites downstream judgments that might otherwise be unrelated? Experiment 9 explored this question at the participant-level, asking whether an individual's aesthetic preferences for complex stimuli are correlated across domains.

Our approach in this experiment neither explicitly (as in Experiments 1–7) nor implicitly (as in Experiment 8) invited participants to map stimuli of one domain to stimuli of another. Rather, this experiment explored whether judgments within each domain emanate from a more general type-independent preference that is stable within an individual. A large body of work finds strong relationships between complexity and aesthetics across a broad range of stimuli, including abstract art (Osborne & Farley, 1970), geometric shapes (Sun & Firestone, 2022a), melodies (Beauvois, 2007; Delplanque et al., 2019), and even food (Lévy et al., 2006). However, are complexity-driven aesthetic preferences consistent across domains? For example, if someone prefers to view especially complex geometric shapes, does that same person also prefer to hear especially complex melodies (Figure 4A)? If so, this would be consistent with a unified representation of complexity that gives rise to an individual 'information density' preference in any given domain.

Recent evidence points to the possibility that other sorts of aesthetic preferences are stable across domains (Chen et al., 2022). Here, we apply a similar approach to our questions about complexity. In Experiment 9, participants completed an aesthetic preference task. On each trial, participants were presented with two stimuli from a given domain (geometric shapes, dot-arrays, melodies, letter-strings, and mathematical expressions; as used in Experiments 1–5) and chose which one they found more (or less) beautiful. Importantly, across trials, the domains varied randomly; for example, on one trial, a participant would choose between two geometric shapes, and on another, they would choose between two mathematical expressions (Figure 4B). This approach yielded individual participant-level aesthetic preferences in many different domains (Figure 4C).

The results of this task were consistent with a stimulus-independent preference applying across domains. An intraclass correlation revealed consistent individual differences in complexity-driven aesthetic preferences across domains (two-way ICC(C,5) = 0.37, $F(149, 596) = 1.58$, $p < 0.001$, 95% CIs = [0.19, 0.51]; Figure 4D). In other words, the stronger a participant's preference for, say, complex shapes, the stronger their preference for complex dot-arrays, melodies, words, and mathematical expressions. Additionally, we computed two permutation measures of consistency, asking whether participants' preferences across domains were more consistent than what would be expected by chance. In each iteration of this test, we shuffled the values (or ranks) across participants within a domain; then, we computed the new mean absolute error for each participant on these shuffled values. Finally, we compared the permuted errors to the real errors, and found that the observed cross-domain consistency was higher than the permuted cross-domain consistency in 1000/1000 iterations when considering the raw values (and 999/1000 iterations when considering the ranks; Figure 4E). Thus, individual complexity preferences were more consistent across domains than what would be expected by chance.

Note that this result is difficult to explain by a mere experimental demand to map complexity across domains. Even more so than in Experiment 8, such a demand was completely absent, especially given that (a) only a single domain appeared within a given trial, and (b) there was no reward to earn (nor even a correct answer to give). In other words, the experimental design does not (and even could not) invite any ad hoc mapping or aligning across domains. Rather, these behaviors, perhaps more so than any other reported here, indicate a more general, unified ‘source’ from which such judgments emanate.

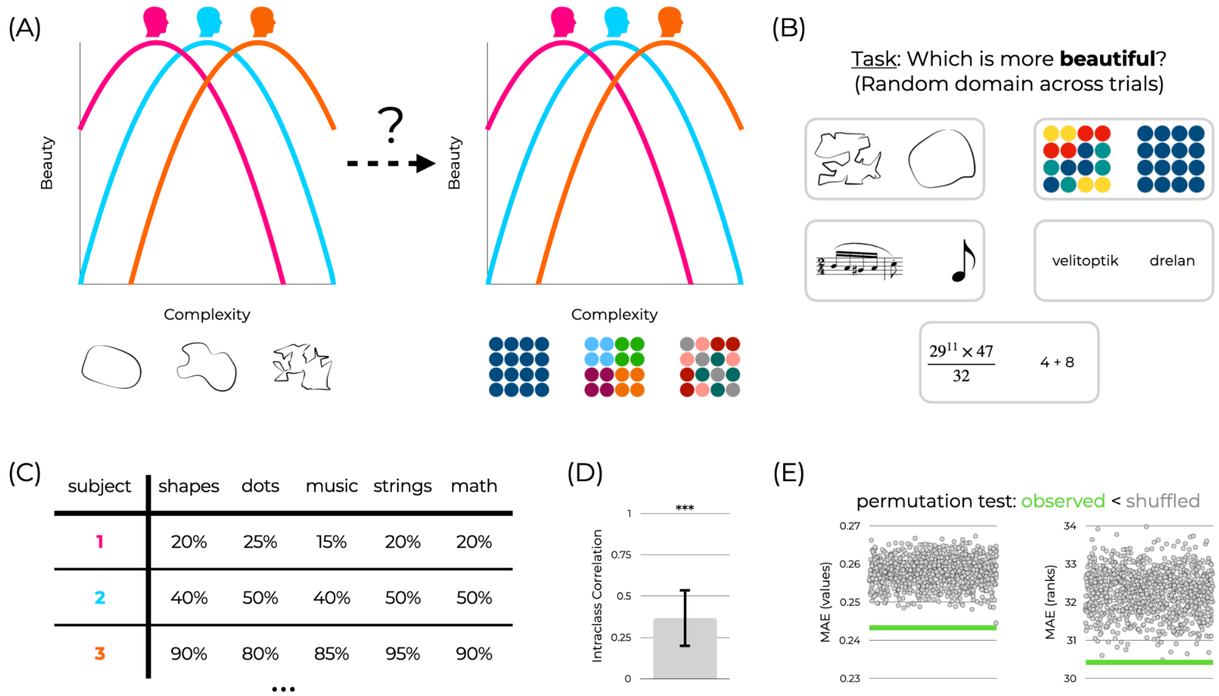

Fig 4. Individuals have stable complexity preferences across domains. (A) Previous work shows an inverted U-shape relationship between complexity and beauty (see Berlyne, 1970; Sun & Firestone, 2022a). However, some people prefer more complex stimuli than other people (resulting in differently located peaks in their inverted U). Are such preferences stable within one person across different domains? (B) In Experiment 9 (N = 150 post-exclusions), each trial presented a simple and complex stimulus from a single domain; participants had to say which was more (or less) beautiful. Across trials, the domains varied randomly. (C) The resulting data index participant-level aesthetic preferences across domains (depicted here with idealized data). (D) An intraclass correlation revealed significant individual consistency across domains. In other words, people who preferred complex (or simple) stimuli in one domain preferred complex (or simple) stimuli in other domains. (E) A permutation analysis further examined the individual stability of these preferences across domains. The observed error of our data was considerably lower than the permuted error (shuffling within-domain, across-participants) when considering both raw values (where the observed error was lower than the permuted error in 1000/1000 iterations) and ranks (where the observed error was lower in 999/1000 iterations). In panel (D), the graph depicts the ICC test statistic with 95% confidence intervals; in panel (E), each point represents 1 iteration in our permutation test.

Discussion

The experiments reported here point towards domain-general representation of complexity in cognition, such that the mind represents a shared property across qualitatively different stimuli. We observed successful transfer of complexity across a variety of domains in ways that support reward-learning (Experiments 1–7), intrude on basic judgments (Experiment 8), and even underlie stable individual preferences (Experiment 9). In contrast to how complexity is typically studied in psychology (with different approaches and parameterizations for different stimuli), these results constitute evidence that the mind represents the shared complexity that unifies stimuli from otherwise disparate domains.

The logic of our approach mirrors recent work in other cognitive domains, such as numerical cognition. A longstanding research tradition analyzes the mechanisms, origins, and development of number perception, posing similar questions about the domain-generality of the relevant representations: When we see some number of dots and hear some number of tones (or touch some number of bumps), to what extent does the mind represent the single quantity shared across these domains? An illuminating series of discoveries answered this question by finding transfer across these domains (Gennari et al., 2023; Arrighi et al., 2014; Izard et al., 2009; Starkey et al., 1983; Starkey et al., 1990), much like how we find evidence for a common representation of complexity across domains. Accordingly, the approaches taken here may prove useful for the study of many different kinds of abstract representations across domains or stimuli, such as the abstract representation of ‘boundedness’ across events and objects (Papafragou & Ji, 2023), ‘extent’ across space and time (Yousif & Scholl, 2019), ‘symmetry’ across language and vision (Hafri et al., 2023b), or even ‘randomness’ across different stimulus-formats (Boger et al., 2025).

Complexity and the language of thought

The present results connect to a recent body of experimental work concerning mental compression algorithms (Sablé-Meyer et al., 2021; Sablé-Meyer et al., 2022; for review see Dehaene et al., 2022), which has shed new light on longstanding debates about the format of mental representation. This work has proposed that the cognitive capacities which facilitate representation of geometric shapes, sequences of musical tones, and related stimuli rely on compressing the stimulus into a structured composition of its primitives. Such representations are proposed to take on a language-like format, deriving from a more general ‘language of thought’ (Fodor, 1975; Quilty-Dunn et al., 2023). The language of thought hypothesis posits that the format and structure of mental representations share many properties with natural languages, such as containing discrete constituents that combine systematically to form structured representations, enabling flexible and generative thought.

While the same overarching language of thought may account for cognitive representations in any given domain (geometric shapes, auditory sequences, and so on), the primitives composing the language in each domain differ. The representation of a complex geometric shape consists of symbols like line segments and curves, while the representation of a complex sequence of tones consists of symbols like pitches and amplitudes. By demonstrating successful transfer across a variety of domains, our work makes this connection more explicit. In other words, these representations not only take on a language-like structure but also interface seamlessly across domains.

Importantly, evidence for domain-general representation of complexity does not constitute evidence against the existence of any domain-specific representations of complexity. Indeed, many notions of complexity are definitionally domain-specific, as they cannot apply to other kinds of stimuli (for example, curvature is a useful proxy for the complexity of a shape, but is not even defined when considering the complexity of a melody). Our proposal is only that, regardless of the nature and extent of any domain-specific representations of complexity in the mind, there is a domain-general notion of complexity in the mind that unifies stimuli across domains.

Origins and development

A natural question concerns the developmental origins of domain-general representations of complexity (also mirrored in the case of number; Feigenson et al., 2004). Previous work links complexity with exploration, demonstrating that children attend to and act on stimuli that are neither too simple nor too complex (Berlyne, 1950; Berlyne, 1966; Kidd et al., 2012; Kidd et al., 2014). Additionally, children may have an intuitive notion of entropy, noticing that non-agentive forces (such as the wind) can only increase entropy and disorder, whereas agentive forces (such as people) can either increase or decrease entropy and disorder (Newman et al., 2010). These and other results demonstrate that children represent some notion of complexity, but it remains open how stimulus-general that notion truly is. Would it extend across radically different domains in the ways we find here? Future work may use the same kinds of straightforward reward-transfer tasks (as in Experiments 1–7) to explore this question.

Along these same lines, a further question remains as to the phylogenetic origins of complexity representations. Recent work suggests that the capacity to represent shape complexity via a compression-like algorithm may be a uniquely human quality: Whereas humans distinguish shapes based on rich differences in the shapes' primitives (in ways captured by a symbolic model of shape), baboons distinguish shapes based on the shapes' visual differences alone (in ways captured by a Convolutional Neural Network; Sablé-Meyer et al., 2021). Given this recent work, it may be that non-human primates and other animals fail to represent stimulus complexity in a maximally abstract fashion, and may thus fail at the types of reward-transfer tasks we use here. On the other hand, other evidence suggests that non-human primates possess abstract representations of other quantities such as number and its corresponding operations (Nieder, 2013; for review, see Dehaene et al., 1998), though the nature of these representations is still debated (Biro & Matsuzawa, 2001; Matsuzawa, 2009). Furthermore, recent evidence suggests that monkeys' representations of geometry (those that would be recruited in the complexity tasks used here) rely on similar cognitive processes to their representations of number (Cantlon et al., 2025; see also Dehaene et al., 2025). Thus, it is possible that similar kinds of mechanisms to those that support abstract representations of number may support abstract representations of complexity. Asking whether abstract representations of complexity exist in non-human primate minds thus seems especially fruitful, regardless of the success or failure of the animals on these tasks. In these ways, the present results not only reveal domain-general representation of complexity but raise new questions about its nature and origins in the mind.

Methods

The following sections contain in-depth descriptions of the experiments performed. The designs, sample sizes, exclusion criteria, and analysis methods for every experiment reported here were pre-registered. These pre-registrations — along with stimuli, experiment scripts, data, and analysis scripts — are available at https://osf.io/42umv/. Readers can also experience every experiment for themselves (except for Experiment 7, which was conducted in-person) at https://perceptionresearch.org/complexity_transfer. The experiments were approved by the Homewood Institutional Review Board of Johns Hopkins University.

Participants for Experiments 1–6, 8, and 9 were recruited online via Prolific (for a discussion of the reliability of this participant pool, see Peer et al., 2017). Participants for Experiment 7 were recruited in-person at Johns Hopkins University. Participants were compensated upon completing the experiment.

The reward-learning tasks (Experiments 1–7) are all nearly identical in design, procedure, and analysis; often only the stimuli varied across these experiments. Thus, for those experiments, all elements should be assumed to be the same as in Experiment 1 unless otherwise specified.

We note that, insofar as these findings concern representations of complexity, they also concern representations of 'simplicity' — the absence or inverse of complexity. Simplicity has also been the subject of much study in cognitive science (see Chater, 1999; Chater & Vitányi, 2003; Feldman, 2003; Feldman, 2016). Here, we focus on complexity given it is often privileged over simplicity (for example, in visual search; Sun & Firestone, 2021; Boger & Keil, 2025) — but these results similarly apply to simplicity. (We thank a reviewer for prompting this discussion.)

Experiment 1: Transfer between geometric shapes and dot-arrays

Experiment 1 tested bidirectional transfer between geometric shapes and dot-arrays in a reward-learning task. We asked whether participants who learned that more (or less) complex shapes yielded greater rewards would spontaneously choose more (or less) complex dot-arrays (or vice versa) in a single, one-shot transfer trial.

This study was pre-registered on October 22, 2024 (https://aspredicted.org/g4yb-qbvq.pdf).

Stimuli and procedure.

At the start of the experiment, participants were randomly assigned to be rewarded for selecting either the simple stimulus or the complex stimulus on each learning trial. Additionally, the learning stimulus class was randomly assigned for each participant (either geometric shapes or dot-arrays, with the other stimulus class being the transfer stimulus).

Participants completed 12 learning trials. On each trial, participants chose between two options on the screen (left or right) and received feedback regarding their choice. If participants chose the correct option, they heard a ‘ding’ sound, and saw a virtual coin drop into a piggy bank, thus increasing the ‘coin bank’ by 5 points; if participants chose the incorrect option, they heard a negative buzzer sound, and saw no change in the coin bank. After 12 learning trials, participants completed a single transfer trial in which a new stimulus class was presented. This key transfer trial was the main target of our analyses.

The geometric shapes used in this experiment were drawn from Sun & Firestone (2022a). The dot-array stimuli were inspired by Sun & Firestone (2022b), but were generated anew for this experiment.

Analyses and results.

As per our pre-registered analysis plans, participants were excluded if they did not submit a complete dataset, or if they earned the reward on less than 50% (6 of 12) learning trials. Additionally, we excluded trials with a response time below 200ms. 101 participants completed the task (one more than our pre-registered sample size participated, due to a feature of Prolific’s recruiting process), 6 of which were excluded by our criterion for the learning trials. Of the remaining 1235 trials, 5 were excluded by the response time criterion.

86.3% of participants transferred the reward-rule to the new, unseen stimulus class ($p < 0.001$ in exact binomial test, $N = 95$, 95% CIs = [77.8%, 92.5%]).

<u>Experiment 2: Transfer between geometric shapes and melodies</u>

Experiment 2 used the same design as Experiment 1, but used melodies instead of dot-arrays. Thus, this experiment tested bidirectional transfer across the visual and auditory modalities.

This study was pre-registered on October 28, 2024 (https://aspredicted.org/yvvs-36v9.pdf).

Stimuli and procedure.

The experiment’s design was identical to that of Experiment 1. The only difference was that the melodies replaced the dot-arrays. On those trials, the two options were presented as music notes on each side of the screen. Clicking on a music note would play a melody; after listening to both melodies, participants chose which one they thought would earn a reward. The simple melodies contained only a single note, while the complex melodies contained multiple notes with varying tempos and pitches. Melodies were generated in Ableton.

Analyses and results.

1 participant was excluded for not submitting a complete dataset, and 3 additional participants were excluded for failing to earn the reward on at least 50% of learning trials. 1 trial (of 1248 remaining) was excluded for speed.

71.9% of participants transferred between the geometric shapes and the melodies ($p < 0.001$ in exact binomial test, $N = 96$, 95% CIs = [61.8%, 80.6%]).

Experiment 3: Transfer between geometric shapes and letter-strings

Experiment 3 tested bidirectional transfer between geometric shapes and letter-strings.

This study was pre-registered on November 12, 2024 (https://aspredicted.org/pyz3-trtv.pdf).

Stimuli and procedure.

For the letter-strings, we drew from (and added to) the exact stimuli used in Lewis & Frank (2016). Complex letter-strings were 4 syllables long, while simple letter-strings were 2 syllables long (as in Lewis & Frank, 2016). To reach 12 simple and 12 complex letter-strings, we generated additional strings that fit these restrictions.

Analyses and results.

101 participants completed the task (one more than our pre-registered sample size participated, due to a feature of Prolific's recruiting process). 10 were excluded by our learning phase criterion; 22 of the remaining 1183 trials were excluded for speed.

78.0% of participants transferred between the geometric shapes and the letter-strings ($p < 0.001$ in exact binomial test, $N = 91$, 95% CIs = [68.1%, 86.0%]).

Experiment 4: Transfer between geometric shapes and mathematical expressions

Experiment 4 tested bidirectional transfer between geometric shapes and mathematical expressions.

This study was pre-registered on January 28, 2025 (https://aspredicted.org/7bh9-86xn.pdf).

Stimuli and procedure.

The simple and complex mathematical expressions within each trial contained identical terms, and only differed in their operations. Both expressions contained 4 unique integers between 11 and 49. The integers were randomly generated, while ensuring they were not divisible by 10 and were not multiples of each other. The simple mathematical expression merely added the four terms together, while the complex one included a variety of operations (namely, exponentiation, multiplication, and division). For example, a simple expression might be $17 + 13 + 24 + 31$, and the accompanying complex expression would be $\frac{17^{13} \times 24}{31}$.

Note that this is just one of many possible ways to operationalize mathematical complexity. We designed our stimuli in this manner because they hold many features constant (including the numbers in each expression and the length of each expression) and vary only in the operations used. However, we think it is likely that mathematical complexity works in other fashions too. For example, perhaps $\sqrt{\pi}$ is more complex than $1 + 1 + 1 - 1$, even though the latter is longer and contains more operations than the former. Still, the former may feel more complex because it is harder to compute. (We thank a reviewer for prompting this discussion.)

Analyses and results.

100 participants completed the task. 2 participants were excluded for failing to learn the reward-rule, and 3 of 1274 remaining trials were excluded for speed.

64.3% of participants transferred the reward-rule between the geometric shapes and the mathematical expressions (p = 0.006 in exact binomial test, N = 98, 95% CIs = [54.0%, 73.7%]).

Experiment 5: Transfer between all pairs of previous stimuli

Experiment 5 tested whether transfer would arise between all of the stimuli used in previous experiments. In other words, the previous experiments tested bidirectional transfer between geometric shapes and a host of other stimuli; but this leaves open the question of whether transfer arises between any pair of stimuli (and not just ones that include geometric shapes).

This study was pre-registered on February 6, 2025 (https://aspredicted.org/2pbb-gxy4.pdf).

Stimuli and procedure.

This experiment contained 5 possible stimulus classes, each of which were used in Experiments 1–4 (geometric shapes, dot-arrays, melodies, letter-strings, and mathematical expressions). A random stimulus class was selected for the learning phase, and then the transfer phase consisted of a single trial of each of the 4 held-out stimulus classes (without feedback). As before, the learning stimulus was chosen randomly for each participant, as was the reward-rule (reward-simple or reward-complex). In this way, the design of this experiment is identical to Experiments 1–4, except that the transfer phase now consisted of 4 trials (1 for each held-out stimulus class) instead of 1.

Analyses and results.

Of the 499 participants who submitted full data for this experiment, 40 were excluded by the learning phase criterion. 13 of the remaining 7344 trials were excluded for speed.

Our first pre-registered analysis tested whether every stimulus class produced successful transfer. Thus, we conducted t-tests to ask whether the mean transfer accuracy across all 4 transfer trials was above-chance for participants who were presented with any of our stimulus classes in the learning phase. In each case, we observed above-chance transfer. The mean transfer accuracy for each class was as follows: shapes: 74.3%, $t(111) = 9.56$, $p < 0.001$, $d = 0.90$, 95% CIs = [69.3%, 79.4%]; dot-arrays: 68.6%, $t(81) = 5.84$, $p < 0.001$, $d = 0.65$, 95% CIs = [62.3%, 74.9%]; melodies: 81.0%, $t(80) = 11.35$, $p < 0.001$, $d = 1.26$, 95% CIs = [75.5%, 86.4%]; letter-strings: 65.8%, $t(90) = 4.83$, $p < 0.001$, $d = 0.51$, 95% CIs = [59.3%, 72.4%]; mathematical expressions: 61.0%, $t(92) = 3.62$, $p < 0.001$, $d = 0.38$, 95% CIs = [55.0%, 67.1%].

Our second pre-registered analysis asked whether every stimulus class was the 'target' of successful transfer. Thus, we conducted exact binomial tests comparing the mean transfer accuracy for any given transfer stimulus to chance. We again observed above-chance transfer in every case: shapes: 78.0%, $p < 0.001$ in exact binomial test, $N = 346$, 95% CIs = [73.3%, 82.3%]; dot-arrays: 73.7%, $p < 0.001$, $N = 376$, 95% CIs = [68.9%, 78.1%]; melodies: 63.8%, $p < 0.001$, $N = 378$, 95% CIs = [58.7%, 68.6%]; letter-strings: 65.5%, $p < 0.001$, $N = 368$, 95% CIs = [60.4%, 70.3%]; mathematical expressions: 70.4%, $p < 0.001$, $N = 365$, 95% CIs = [65.4%, 75.0%].

Our final pre-registered analysis asked whether successful transfer arose between each stimulus pair. Thus, we conducted 10 binomial tests on transfer accuracy, one for each possible learning-transfer pair. We observed significantly above-chance transfer in 9/10 of these pairs: dot-arrays and mathematical expressions: 64.0%, $p < 0.001$ in exact binomial test, $N = 175$, 95% CIs = [56.4%, 71.1%]; dot-arrays and melodies: 75.5%, $p < 0.001$, $N = 163$, 95% CIs = [68.1%, 81.9%]; dot-arrays and shapes: 82.5%, $p < 0.001$, $N = 194$, 95% CIs = [76.4%, 87.5%]; dot-arrays and letter-strings: 62.2%, $p = 0.002$, $N = 172$, 95% CIs = [54.5%, 69.5%]; mathematical expressions and melodies: 65.3%, $p < 0.001$, $N = 173$, 95% CIs = [57.5%, 72.4%]; mathematical expressions and shapes: 75.6%, $p < 0.001$, $N = 205$, 95% CIs = [69.1%, 81.3%]; melodies and shapes: 74.1%, $p < 0.001$, $N = 193$, 95% CIs = [67.3%, 80.1%]; melodies and letter-strings: 72.1%, $p < 0.001$, $N = 172$, 95% CIs = [64.8%, 78.7%]; shapes and letter-strings: 71.8%, $p < 0.001$, $N = 202$, 95% CIs = [65.0%, 77.9%]; only mathematical expressions and letter-strings failed to reach statistical significance, but this pair was still numerically above chance: 56.5%, $p = 0.090$, $N = 184$, 95% CIs = [49.0%, 63.8%]. When correcting for multiple comparisons (via either Bonferroni correction or Holm correction), 9/10 pairs still show significantly above-chance transfer.

Experiment 6a: Transfer for complexity, but not saturation

Experiment 6a asked whether transfer would arise for merely any stimulus dimension, and not just those having to do with complexity. To test this, we re-used the design of Experiment 1 but added a key color transfer trial. Notably, colors can vary in a stimulus dimension (here, saturation) that is not necessarily related to complexity. Thus, we predicted that no transfer would arise for saturation.

This study was pre-registered on February 25, 2025 (https://aspredicted.org/59c7-jrsw.pdf).

Stimuli and procedure.

This design exactly replicated that of Experiment 1, but added one key transfer trial. In this additional transfer trial, participants were presented with two colors of identical hue and lightness (in HSL space), but of differing saturation. (The hue was chosen randomly for each participant, and the lightness was always 50%.) The more saturated color had 75% saturation, compared to the less saturated color's 25%. Importantly, colors could never be chosen as the learning stimulus; the learning stimulus could only be geometric shapes or dot-arrays, as in Experiment 1.

In this experiment (and in Experiments 6b and 6c), we did not test transfer from the 'control' stimuli (in this case, saturated vs. desaturated colors) to shapes and dot-arrays. This is because any result in this case would be difficult to interpret without direct comparison to a case where transfer is present (which is precisely what examining bidirectional transfer between shapes and dot-arrays allows for).

Analyses and results.

99 participants submitted full data, and 3 participants were excluded due to the learning phase criterion. 20 of the remaining 1344 trials were excluded for speed; one of these trials was a transfer trial, which explains why the degrees of freedom for the paired *t*-test that follows is 94 (as opposed to 95).

First, we observed that participants transferred between the geometric shapes and dot-arrays, as they did in Experiment 1 (at a rate of 84.4%, $p < 0.001$ in exact binomial test, $N = 96$, 95% CIs = [75.5%, 91.0%]). However, participants did not transfer from either of these stimuli to saturation; in other words, performance was indistinguishable from chance on the saturation transfer trials (with 48.4% of participants earning the reward, $p = 0.838$, $N = 95$, 95% CIs = [38.0%, 58.9%], BF10 = 0.26). Additionally, participants were significantly more accurate on the non-saturation (here, geometric shape or dot-array) transfer trial than they were on the color transfer trial (mean difference = 35.8%; $t(94) = 5.99$, $p < 0.001$, $d = 0.62$, 95% CIs = [23.9%, 47.6%]).

Experiment 6b: Transfer for complexity, but not brightness

Experiment 6b replicated Experiment 6a, but used brightness instead of saturation. Because brightness is unrelated to complexity (but is still a dimension for which one can have 'more' or 'less' magnitude), we predicted that no transfer would arise to brightness.

This study was pre-registered on January 21, 2026 (https://aspredicted.org/ud8zk2.pdf).

Stimuli and procedure.

This design exactly replicated Experiment 6a; but instead of an additional transfer trial depicting colors differing in saturation (with identical hue and lightness in HSL space), here the additional transfer trial depicted two gray squares differing in brightness. The darker square had 25% lightness, and the lighter square had 75% lightness. Additionally, the experiment itself used a darker background (here, 50% lightness) than our other experiments such that the two squares had the same contrast relative to the background.

Analyses and results.

100 participants submitted full data, 1 of which was excluded due to the learning phase criterion. 1 trial (of 1386 remaining) was excluded for speed.

As before, participants transferred between the geometric shapes and dot-arrays (at a rate of 81.8%, $p < 0.001$ in exact binomial test, $N = 99$, 95% CIs = [72.8%, 88.9%]). However, there was no transfer from either of these stimuli to brightness (43.4% transfer, $p = 0.228$, $N = 99$, 95% CIs = [33.5%, 53.8%], BF10 = 0.54). The difference between the brightness and non-brightness (shape or dot-array) transfer trials was significant (mean difference = 38.4%; $t(98) = 6.18$, $p < 0.001$, $d = 0.62$, 95% CIs = [26.1%, 50.7%]).

Experiment 6c: Transfer for complexity, but not size

Experiment 6c again replicated Experiment 6a, this time using size instead of saturation.

This study was pre-registered on January 21, 2026 (https://aspredicted.org/ze8uq2.pdf).

Stimuli and procedure.

This design exactly replicated Experiment 6a, but replaced the saturation transfer trial with a size transfer trial. On the size transfer trial, participants were presented with two black squares that differed in size — the larger square had 16x the area of the smaller square.

Analyses and results.

99 participants submitted full data; 2 were excluded due to the learning phase criterion; and 1 trial (of 1358 remaining) was excluded for speed.

We observed successful transfer between geometric shapes and dot-arrays (at a rate of 83.5%, $p < 0.001$ in exact binomial test, $N = 97$, 95% CIs = [74.6%, 90.3%]). Similarly, we observed no transfer to size (49.5%, $p = 1.000$, $N = 97$, 95% CIs = [39.2%, 59.8%], BF10 = 0.25); and the difference between the size and non-size transfer trials was significant (mean difference = 34.0%, $t(96) = 5.21$, $p < 0.001$, $d = 0.53$, 95% CIs = [21.0%, 47.0%]).

Experiment 7: Transfer between tactile forms and dot-arrays

Experiment 7 tested transfer to a new modality: touch. Here, we asked whether bidirectional transfer would arise between tactile forms (which participants had no visual access to) and dot-arrays as in previous experiments.

This study was pre-registered on April 29, 2025 (https://aspredicted.org/ttpz-fwwf.pdf).

Stimuli and procedure.

We used the same design here as in the other transfer experiments: Participants completed 12 learning trials, followed by 1 transfer trial. The dot-arrays were the same ones used in previous experiments. We 3D printed 12 simple shapes and 12 complex shapes (selected from the shapes used in previous experiments) with a Bambu Lab X1C, and used those as our tactile forms. The tactile shapes were not filled (they were simply outlines that could be grasped and lifted up from the inside), much like how their visual counterparts (used in previous experiments) were outlines with no visual fill in the center.

Participants were recruited in-person at Johns Hopkins University. For the tactile trials, the experimenter placed one shape in each of two cardboard boxes. Each box contained holes in both sides, allowing participants to touch the shapes. However, participants had no visual access to the shapes; thus, they made their judgments purely based on tactile information. As in the online experiments, participants received auditory feedback indicating whether or not they earned a reward on each turn. For the dot-array trials, participants used the experimenter's computer to input their responses.

Analyses and results.

We recorded data from 99 participants (an error in the server used to store participant data from the experimenter's computer prevented data recording for 1 additional participant). 0 participants were excluded for responding correctly on less than 50% of trials in the learning phase. 4 trials were excluded for speed. (Participants completed the dot-array trials using the experimenter's computer and keyboard. Thus, fast keypresses were possible, in much the same way as in the previous experiments. However, none of the tactile shape trials were excluded for speed.)

81.8% of participants transferred the reward-rule between the tactile forms and the dot-arrays ($p < 0.001$ in exact binomial test, $N = 99$, 95% CIs = [72.8%, 88.9%]).

Experiment 8: Automatic interference in a Stroop-like task

Experiment 8 tested whether representations of complexity in one domain automatically intrude on basic judgments of complexity in another domain.

This study was pre-registered on January 22, 2025 (https://aspredicted.org/skyd-v2z5.pdf).

Stimuli and procedure.

We designed a modified Stroop task. On each trial, participants were presented with two words — one simple and one complex — and simply had to choose which one was more complex in one block, and more simple in another. (The order of the two blocks was randomized for each participant; we used a blocked design to ensure that any observed effects did not merely arise because of a preference for choosing the complex or simple words.) Each block contained 120 trials. The words used were the same as those used in Experiment 3, with the addition of several new words that followed the same rule as in that experiment (complex words have 4 syllables, simple words have 2 syllables).

Importantly, above each word, a task-irrelevant shape appeared (from the shapes used in Experiment 1). Participants were instructed only to judge the words, and that they could totally ignore the shapes. On one half of trials, a complex shape appeared above the complex word, and a simple shape appeared above the simple word, such that shape complexity was 'congruent' to word complexity. On the other half of trials, a complex shape appeared above the simple word, and the simple shape appeared above the complex word, such that shape complexity was 'incongruent' to word complexity. Each block contained an equal number of congruent and incongruent trials, and the order of these trials was randomly shuffled for each participant.

Analyses and results.

We recruited 50 participants. 1 participant did not submit a full dataset, and 1 additional participant was excluded by our pre-registered accuracy criterion (which excluded participants who gave the correct answer on less than 75% of trials). Of the 11520 trials remaining, 456 (3.96%) were excluded by our pre-registered response time criterion (which excluded trials with a response time below 200ms or above 1500ms).

As one would expect if representations of complexity interfere with basic judgments across domains, participants were faster on congruent shape-word trials than incongruent shape-word trials (57.4ms difference, $t(47) = 9.07$, $p < 0.001$, $d = 1.31$, 95% CIs = [44.7, 70.1] in paired *t*-test). And this was not just the result of a speed-accuracy tradeoff; in fact, participants were also more accurate on congruent trials (mean difference: +2.49%, $t(47) = 3.26$, $p = 0.002$, $d = 0.47$, 95% CIs = [0.96%, 4.03%]).

Experiment 9: Stable individual differences in aesthetic judgments

Experiment 9 tested whether domain-general representations of complexity govern stable individual differences in aesthetic judgments across those domains.

This study was pre-registered on February 18, 2025 (https://aspredicted.org/pppj-xqmr.pdf).

Stimuli and procedure.

On each trial of this experiment, participants were presented with a simple and complex stimulus of a given type. In one block, participants were asked to choose which option they found more beautiful; in the other block, they were asked to choose which option they found less beautiful. (The purpose of this blocked design was to ensure that any observed effects do not arise due purely to a preference to choose the complex option. The order of the two blocks was randomized for each participant.) Each trial presented only one stimulus class, but across trials the stimulus classes varied randomly; for example, one trial might depict two geometric shapes, while the next might contain two mathematical expressions. We used the 5 stimulus classes from Experiment 5 (geometric shapes, dot-arrays, melodies, letter-strings, and mathematical expressions). Each block contained 30 trials, allowing for each of the 5 stimulus classes to appear 6 times. Trial order within a given block was randomized for each participant.

Analyses and results.

All 150 participants submitted a full dataset, and we pre-registered no participant-level exclusion criteria. 48 of the 9000 trials were excluded based on our pre-registered response time exclusion criterion (which excluded trials with a response time below 200ms).

First, we computed an intraclass correlation coefficient, which revealed consistent individual differences in complexity-driven aesthetic preferences across domains (two-way ICC(C,5) = 0.37, $F(149, 596) = 1.58$, $p < 0.001$, 95% CIs = [0.19, 0.51]).

Next, we conducted two permutation analyses of this reliability. These tests allowed us to better understand the observed stability relative to chance. The basic intuition for these tests is to compare the observed within-participant consistency to the level of consistency that would arise after shuffling all preferences within-domain, across-participants. So, we conducted a simulation in which, in each of 1000 iterations, we shuffled the values within-domain, across-participants. Then, on these shuffled values, we computed a new 'mean absolute error' — here, the difference between a participant's preference in a given domain and their average preference across domains. We compared these values to the observed mean absolute error in our data. First, we performed this analysis for the raw values (analyzing how often a participant found the complex option more beautiful within a domain); this revealed a high level of stability, as our observed error was lower than the permuted error in 1000/1000 iterations. Second, we performed this analysis for ranked values; here, our observed error was lower than the permuted error in 999/1000 simulations. Thus, these results point to the stability of complexity-driven aesthetic preferences across domains.

Data availability

All data are available via OSF at https://osf.io/42umv/.

Code availability

All code is available via OSF at https://osf.io/42umv/.

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Author contributions

T.B. and C.F. contributed equally to the study's conceptualization, methodology, visualization, writing—original draft, and writing—review and editing. T.B. served as lead for data curation and formal analysis. C.F. served as lead for project administration and supervision.

Competing interests

The authors declare no competing interests.

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