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Mechanistic Complexity Is Fundamental: Evidence From Judgments, Attention, and Memory

Tal Boger[1] and Frank C. Keil[2]
[1] Department of Psychological and Brain Sciences, Johns Hopkins University
[2] Department of Psychology, Yale University

What makes an object *complex*? Complexity comes in many different forms. Some objects are *visually* complex but *mechanistically* simple (e.g., a hairbrush). Other objects are the opposite; they look simple but work in a complex way (e.g., an iPhone). Is one kind of complexity more fundamental to how we represent, attend to, and remember objects? Although most existing psychological research on complexity focuses on visual complexity, we argue that mechanistic complexity may be more consequential: Across five preregistered experiments ($N = 780$ adults), we show that mechanistic complexity not only predicts explicit judgments but also drives visual attention and memory. Thus, representations of object complexity—and object representations more broadly—rely on more than just external appearance.

Public Significance Statement
Every day, we are struck by the complexity of our surroundings. Complexity affects us both directly—for example, when thinking about how the parts in a machine work—and indirectly—for example, when appreciating the beauty of a painting. But what makes an object complex? The way it looks? Or the way it works? We show that mechanistic complexity—the kind of complexity *beneath* an object's surface—is the more fundamental kind of object complexity in the mind. In other words, our representations of objects may be more than meets the eye.

Keywords: complexity, object representation, mechanism, perception

Which is more complex: a bicycle or a car? When faced with this question, most people answer a car. But how do we make such a judgment? What information do we use? Reasoning about the "complexity" of an object may imply many different thoughts or judgments; the car contains more complex inner workings than the bicycle (mechanistic complexity), but the bicycle looks more complex than the car, at least in silhouette (visual complexity).

In other words, complexity comes in many different *kinds*. Both appearance and mechanism correspond to different kinds of object complexity. Other kinds of object complexity exist too, such as functional complexity (the complexity of what something can do; Ahl & Keil, 2017). Sometimes, these differing notions of object complexity are in harmony, as when we appreciate that a helicopter is more complex than a skateboard. But other times, these notions *compete* (e.g., bicycle vs. car). In these cases, it is unclear what it means for an object to be "complex" or which notion of complexity wins out over the other (if at all).

We seem to integrate these different kinds into an intuitive understanding of object complexity. How? And what might the downstream consequences of this be? One possibility is that among these competing kinds of complexity, one is more fundamental, meaning that it may dominate our intuitions and even affect implicit cognitive or visual processes more than another kind. Uncovering a preference for one kind of complexity would illuminate how we arrive at these intuitive judgments and reveal signatures of object representations more broadly. Here, we compare visual and mechanistic complexity to ask which kind informs our representations of object complexity.

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Tal Boger https://orcid.org/0000-0002-5476-8416
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Correspondence concerning this article should be addressed to Tal Boger, Department of Psychological and Brain Sciences, Johns Hopkins University, 3400 North Charles Street, Baltimore, MD 21218, United States. Email: tboger1@jhu.edu

Complexity in Our Lives

Complexity drives many of our thoughts every day. For example, when an object breaks or malfunctions, we may consider whether it is too complex to fix on our own—making an intuitive judgment of mechanistic complexity (Kominsky et al., 2018). We may view someone as an "expert" in a field if they are able to describe how a complex system works, as opposed to just describing how it looks (Hmelo-Silver & Pfeffer, 2004). When in an art gallery, we may find some paintings too complex or too simple to be beautiful; instead, we appreciate paintings in a sort of complexity "sweet spot" (Osborne & Farley, 1970; Sun & Firestone, 2022a).

We make these judgments for all kinds of stimuli—not just visual objects. We enjoy the complexity of musical passages; we notice the complexity of physical actions, such as the shooting motion of a basketball player; and we appreciate the complexity of foods with subtle, complementing flavors. More abstractly, biological and social systems may be complex (Csete & Doyle, 2002; Kappeler, 2019). Thus, complexity is prevalent both within the domain of the objects and outside of it.

Importantly, research on object complexity goes beyond explicit judgment, revealing that complexity drives some implicit and automatic behaviors. For example, previous work establishes links between complexity and memory (Alvarez & Cavanagh, 2004; Mathy & Feldman, 2012), complexity and aesthetic preference (Osborne & Farley, 1970; Sun & Firestone, 2022a), complexity and attention (Sun & Firestone, 2021), and even complexity and children's ability to learn from television (Welch & Watt, 1982). Complexity also relates to language; we map longer words to more complex objects (Lewis & Frank, 2016), and complexity affects the length of our object descriptions (Sun & Firestone, 2022b). Finally, complexity also affects concept learning (Feldman, 2000, 2003; Ward et al., 2013). Thus, complexity has many implicit uses that are crucial to cognition.

Perhaps even more immediately, complexity is crucial to the play, exploration, and curiosity of both humans and animals (Berlyne, 1960, 1966). We seek stimuli (ranging from toys to books to conversations) that pique our interest—and one way to conceive of this interest is via complexity. Therefore, complexity is a key and unavoidable part of the natural world (Rescher, 1998). It affects how we see, learn, and remember.

Complexity in Psychology

Despite the importance of object complexity, the concept remains underdefined in psychology. Many works fundamental to the study of complexity avoid defining the term, instead opting to contextualize it with similar concepts (e.g., in a seminal discussion of complexity, Berlyne, 1966, often either wrote "complexity" in scare quotes or invokes "the properties that we designate by words like novelty, surprisingness, incongruity, *complexity*, variability, and puzzlingness"). An expansive research tradition explores different kinds of object complexity in isolation and asks how each kind affects behavior. However, these works do not explore how different kinds relate to each other or combine to form our understanding of object complexity. In other words, the building blocks of our representations of object complexity remain underexplored.

In psychological studies of complexity, the term "complexity" is often synonymous with visual complexity. For example, according to bibliometric data, since 2020, over 7,730 articles discuss visual complexity in psychology, compared to around 100 for mechanistic complexity and fewer than 3,000 for "conceptual complexity" (an umbrella term encompassing higher level forms of complexity, such as mechanistic complexity, functional complexity, etc.).[1] A likely cause for this is that various mathematical proxies exist for visual complexity, such as "visual clutter" (Rosenholtz et al., 2007), file size (Madan et al., 2018), shape skeletons (Feldman & Singh, 2006; Sun & Firestone, 2021), and more. Each of these definitions can easily be computed from an image, making visual complexity an accessible computational metric.[2]

Computational definitions of this sort do not exist for conceptual complexity. Though some reasonable proxies exist (e.g., number of parts, number of interactions between parts), it is hard to programmatically apply them to batches of images. These proxies would also be difficult for an algorithm to generalize to different kinds of stimuli (e.g., abstract objects, stimuli whose inner mechanisms are not visible). Perhaps for this reason, conceptual complexity has been relatively ignored.

While psychological research on object complexity is biased toward an object's appearance over its mechanism, our everyday lives may tilt the other way. Philosophical analyses of the nature of "complexity" suggest that we rely on mechanistic complexity often, as it is tied to how we interact with the world. Understanding mechanisms is crucial to any society for building and repairing objects (Rescher, 1998). This idea is supported by work in developmental psychology suggesting that children are sensitive to the internal mechanisms of their surroundings (Lockhart et al., 2019; Simons & Keil, 1995) and that mechanistic representations may even be innate (Leslie, 1994). Still, visual complexity has its uses too. Research suggests that visual complexity drives implicit processes such as visual attention and curiosity (Sun & Firestone, 2021). In this way, visual complexity may serve a functional role, signaling to us which objects are worth exploring. However, while these uses are important, they may not be as crucial as understanding mechanistic complexity, which more directly affects our ability to interact with objects. Thus, mechanistic complexity may play a larger role in our lives than visual complexity.

Here, we ask: Do our judgments of object complexity rely on mechanistic information more than visual information? Furthermore, might mechanistic complexity be so important that it even affects *implicit* processes—in other words, driving processes previously thought to be affected only by visual complexity, such as visual attention and visual working memory?

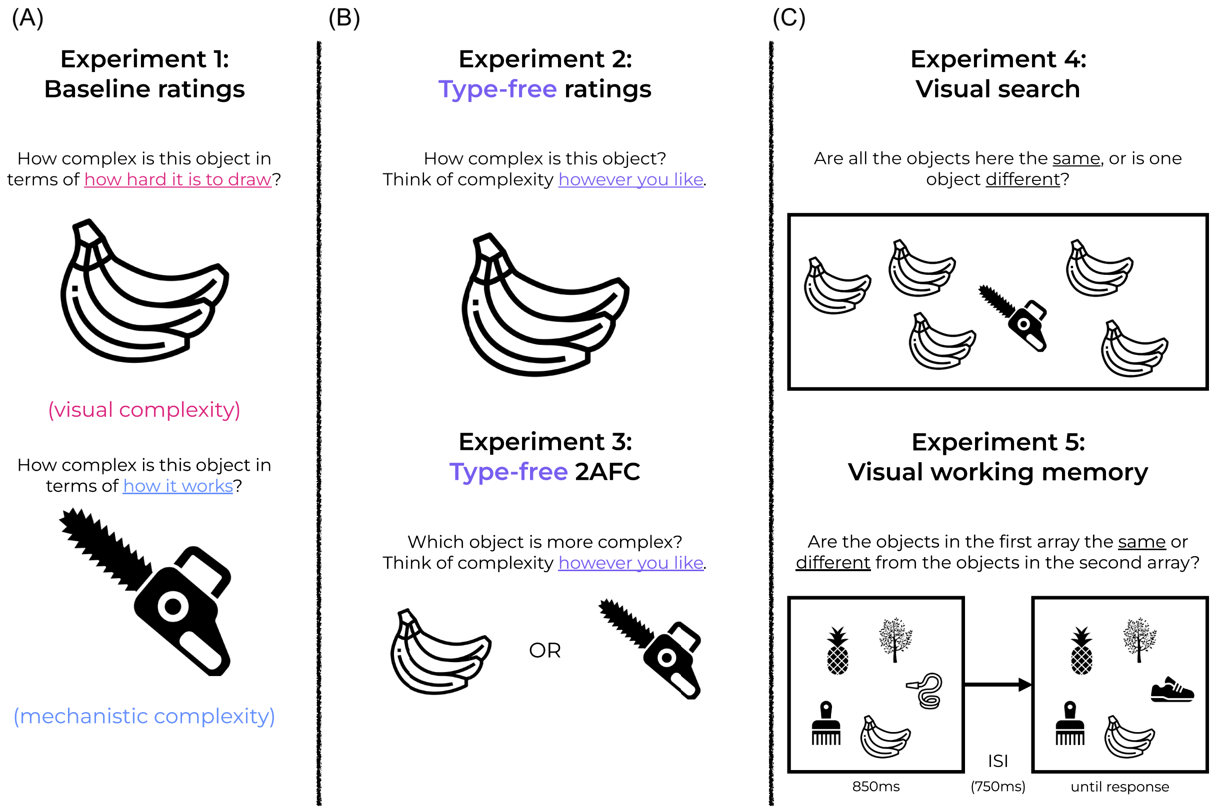
The Present Experiments

In five preregistered experiments (depicted schematically in Figure 1), we find that mechanistic complexity is more fundamental than visual complexity for judgment, attention, and memory. By "more fundamental," we mean that it seems to take precedence over visual complexity in driving these processes. In Experiment 1, we

[1] This bibliometric data come from searching Google Scholar with the queries ["visual complexity," psychology], ["mechanistic complexity," psychology], and ["conceptual complexity," psychology].

[2] Note that even in these cases, mathematical definitions of complexity may produce contrasting results; for example, a pattern of noise may have lots of visual clutter but a low file size. Thus, complexity is hard to pin down even computationally.

Figure 1
Schematic Illustration of Our Five Experiments



Note. (A) In Experiment 1, we gathered baseline ratings for visual and mechanistic complexity to be used in subsequent experiments. Though only silhouette images are depicted here, we gathered ratings across three levels of realism (words with no images, words with silhouette images, and words with real object images). (B) In Experiments 2 and 3, we probed which kind of complexity predicts ratings of type-free complexity. Experiment 2 used the same rating task as in Experiment 1, but this time gathered ratings for type-free complexity (i.e., simply "rate the complexity of the object"). Experiment 3 presented participants with a two-alternative forced-choice (2AFC) task in which they had to say which object is more complex. (C) In Experiments 4 and 5, we asked if mechanistic complexity drives performance in implicit cognitive tasks. Experiment 4 presented participants with a visual search task, and Experiment 5 consisted of a visual working memory task. Interested readers may complete all experiments on our guide page (https://perceptionstudies.github.io/mechanism) and view all materials on our OSF repository (https://osf.io/csfdq/). ISI = interstimulus interval. See the online article for the color version of this figure.

gathered ratings of mechanistic complexity and visual complexity on a set of objects (Figure 1A). We used these ratings as a basis for our later experiments. In Experiment 2, we gathered ratings of "type-free" complexity—ratings of complexity where no single kind is specified in the instructions—and found that these ratings are better predicted by mechanistic complexity than visual complexity. In Experiment 3, we replicated this result with a two-alternative forced-choice task, again finding a preference for mechanistic complexity (Figure 1B).

But as noted previously, complexity does not only affect explicit judgments—it also drives implicit processes (e.g., visual attention as in Sun & Firestone, 2021; visual working memory as in Alvarez & Cavanagh, 2004). These effects are often thought to be associated with visual complexity. Given the visual nature of these tasks, one may expect that mechanistic complexity does not affect performance. However, a final set of experiments suggests that mechanistic complexity may drive these implicit processes more than visual complexity (Figure 1C). Experiment 4 found that mechanistic complexity drives performance in a visual search task more strongly than visual complexity. Experiment 5 found that mechanistic complexity drives visual working memory. Taken together, these results suggest that our representations of object complexity may rely on mechanistic information more than visual appearance.

Interested readers may view the tasks, exactly as our participants completed them, on our guide page (https://perceptionstudies.github.io/mechanism). All experiments were approved by the Yale University Institutional Review Board. Sample sizes, experimental design, and analysis plans for all experiments were preregistered. All of our preregistrations, experimental code, data, and stimuli are available on our Open Science Framework (OSF) repository (https://osf.io/csfdq/).

Experiment 1: Baseline Ratings of Visual and Mechanistic Complexity

In our first experiment, we gathered ratings of visual and mechanistic complexity to use as a baseline for later experiments.

We chose simple proxy definitions of each kind of complexity. We gathered ratings for visual complexity by asking "how complex is the object in terms of how hard it would be to draw" (in line with the number of "turns"; Attneave, 1957) and for mechanistic complexity by asking "how complex the object is in terms of how it works" (a direct definition of the concept). In each condition of this experiment, a set of 50 objects appeared one after another, all in one of three levels of realism: words with no images (i.e., "how complex is a computer in terms of how it works," with no accompanying image), words with accompanying silhouette images (i.e., the previous instruction appearing alongside a line drawing of a computer with no color or depth), and words with accompanying real object images (i.e., the previous instruction appearing alongside a real image of a computer containing color and depth). We used three different levels of realism to ensure our results generalize across different ways of conceptualizing the object in question. For example, one may think that visual complexity ratings differ when one sees an image versus when one just reads the word. (Perhaps the image contains several visually complex contours or features that the participant was not considering when reading the word on its own.) This experiment does not provide insight into whether mechanistic or visual complexity is preferred. Rather, it is a necessary baseline for understanding preferences in later experiments.

Probing Visual Complexity

Initially, it may seem odd to ask participants to judge visual complexity in terms of how hard an object is to draw. After all, why not ask participants to rate visual complexity for an object "in terms of how it looks," creating a parallel with how we probe mechanistic complexity (where participants rate complexity of an object "in terms of how it works")?

This is an issue that several other studies of complexity face; when gathering judgments of visual complexity, previous work either creates long definitions of "complexity" to minimize confusion or provides simple proxies for complexity (for a discussion of these issues, see Sun & Firestone, 2022b). We chose to gather ratings of visual complexity with this drawing-based proxy for a few reasons. First, this is a succinct definition of visual complexity without a long preamble. Second, it is an intuitive instruction: one can imagine how long it would take to draw something or how difficult drawing that thing would be. Third, this metric has precedence in previous work, which shows that drawing difficulty and visual complexity are intricately related. Leeuwenberg (1967) found a near-perfect correlation ($r = 0.97$) between drawing (via reproduction) and visual complexity. (Here, Leeuwenberg, 1967, operationalized "visual complexity" with a theoretical information metric computed over visual patterns, and this metric correlates with subjective judgments of the complexity of the patterns.) Finally, we verify below that this method of probing visual complexity resulted in systematic judgments (i.e., judgments that are stable across stimulus conditions and vary as much as judgments of mechanistic complexity).

Method

Participants

We recruited 20 unique participants for each of three levels of object realism (words only, words with silhouettes, words with real objects) and each of the two types of complexity (visual or mechanistic complexity), resulting in 120 participants total. Participants in all experiments and conditions were unique, such that ratings were independent. Participants were recruited via Prolific (for a discussion of the reliability of this subject pool, see Peer et al., 2017). Participants were compensated upon completion of the experiment.

Stimuli and Procedure

There were three conditions for the form of stimuli: (a) words only, (b) words with silhouette images, and (c) words with real object images. There were two conditions for the instructed form of complexity: (a) visual complexity and (b) mechanistic complexity. In each condition, participants saw all 50 objects in the form corresponding to their assigned condition (i.e., a participant assigned to the silhouettes condition sees all 50 objects as silhouettes) and complexity type (i.e., the participant rates the same type of complexity for all 50 objects). The objects appeared in a randomized order for each participant. All images were 500×500 pixels in participants' web browsers.

On each trial, participants rated the complexity of an object on a scale of 1 (*least complex*) to 9 (*most complex*) using their keyboard (i.e., they would press the number corresponding to the rating). In the visual complexity condition, participants were instructed: "Please rate the visual complexity of [object] (imagine how difficult they would be to draw), 1 being least complex and 9 being most complex." In the mechanistic complexity condition, they were instructed: "Please rate the complexity of a [object] in terms of how it works, 1 being least complex and 9 being most complex."

Participants who did not submit a complete data set were excluded; trials with a response time below 200 ms were excluded for being too fast. Across all conditions, this excluded zero participants and 45 trials (out of 6,000 total).

Results

This experiment was primarily a baseline needed for later experiments.[3] Given that these ratings serve as a basis for later experiments, it is important to check that they are consistent. One way we can test this is by correlating object-wise complexity ratings across stimulus conditions; objects rated as complex in one condition should be rated as complex in the other conditions, too. We observed high correlations across the stimulus conditions for both the mechanistic complexity ratings, correlation across words and silhouettes $r(48) = 0.94$, $p < .001$; silhouettes and real objects $r(48) = 0.94$, $p < .001$; words and real objects $r(48) = 0.92$, $p < .001$, and the visual complexity ratings, correlation across words and silhouettes $r(48) = 0.79$, $p < .001$; silhouettes and real objects $r(48) = 0.77$, $p < .001$; words and real objects $r(48) = 0.90$, $p < .001$.

Both visual and mechanistic complexity ratings were similarly variable. The mean object-wise standard deviations in visual complexity ratings were 1.55, 1.59, and 2.02 in the words, silhouettes,

[3] In an earlier version of this project, we planned to compare illusory effects on visual and mechanistic complexity before asking which kind of complexity is more fundamental. Therefore, the preregistration for this experiment contains predictions and analysis plans for t tests comparing complexity ratings across levels of stimuli realism. Because we preregistered this analysis, we provide the t tests and analyses as listed in the preregistration in our OSF repository: https://osf.io/csfdq/. However, these analyses are left out of the current article.

and real object conditions, respectively; they were 1.80, 1.78, and 1.85 for mechanistic complexity. Thus, differences in subsequent experiments cannot be explained by one kind of complexity being more variable than the other. This also shows that our instructions for visual complexity in fact produce systematic judgments. Therefore, these results serve as a reasonable baseline for later experiments.

Experiment 2: Ratings of Type-Free Complexity

After gathering ratings of mechanistic and visual complexity for each object, we asked: Which kind better predicts ratings of type-free complexity (i.e., ratings of complexity where participants are not instructed to think of one specific kind)? In other words, if we give a new set of participants the same rating task but now ask everyone to simply "rate the complexity of the [object]" (and that they can think of complexity "however [they] like"), will these ratings be more correlated with visual or mechanistic complexity? A preference for either type of complexity may suggest that intuitive ratings of object complexity are more aligned with that type.

Method

Participants

As before, we recruited 20 unique participants for each of our three stimulus conditions, resulting in 60 participants.

Stimuli and Procedure

The design of this experiment was identical to that of Experiment 1, except for the instructions. Rather than being told to rate the visual or mechanistic complexity of an object, participants were told to simply rate its complexity (type-free) and that they could think of complexity however they want. As before, participants made this judgment by pressing the corresponding key on their keyboard from 1 (*least complex*) to 9 (*most complex*).

Trials with response times below 200 ms were excluded for being too fast. There were zero participants excluded and zero trials excluded across each of our three stimulus conditions.

Results

Across all three levels of realism, we observed higher correlations between type-free complexity and mechanistic complexity than between type-free complexity and visual complexity (Figure 2A). Both types of complexity had strong and significant correlations to type-free complexity ratings ($p < .001$ in all correlations), but the mechanistic r values were comparatively higher in each condition: words-only mechanistic $r(48) = 0.94$ versus words-only visual $r(48) = 0.72$; silhouettes mechanistic $r(48) = 0.92$ versus silhouettes visual $r(48) = 0.85$; real objects mechanistic $r(48) = 0.96$ versus real objects visual $r(48) = 0.83$.[4,5]

In other words, intuitive complexity ratings were better predicted by mechanistic complexity than visual complexity. This provides initial evidence for a preference for mechanistic complexity when judging objects.

Experiment 3: Forced-Choice Complexity

Although our previous results point to a preference for mechanistic complexity, it is possible that a rating task taps into complexity in a way that differs from how we experience it every day. When we judge the complexity of an object, we do not do so by rating it from 1 to 9. Rather, we may do so by comparing it to another object (or comparing it to an object in memory, such as when we buy a new phone or computer). Perhaps the previous rating task induced odd task demands that tapped into a different notion of "complexity" (or even task demands unrelated to complexity itself, such as order effects). Here, we addressed these potential issues by presenting participants with a two-alternative forced-choice (2AFC) task instead of a rating task. On each trial, participants said which of two objects (randomly selected from our stimulus set, appearing as words only) is more complex. With these judgments, we generated well-powered ratings of object complexity and then asked whether these ratings aligned more with mechanistic complexity or with visual complexity.

Method

Participants

One hundred new participants were recruited for this study. This sample size was larger than what we used for the rating tasks given that converting 2AFC choices into stable rankings requires more data.

Stimuli and Procedure

Participants performed a simple 2AFC task with 100 trials. On each trial, two objects were chosen at random from our stimulus set, and participants said which is more complex (as before, participants were instructed that they can think of complexity "however you want"). The objects appeared as words only (i.e., no accompanying images). Participants said which object they thought was more complex by pressing a key on their keyboard ("1" if they thought Object 1 was more complex, "2" if they thought Object 2 was more complex).

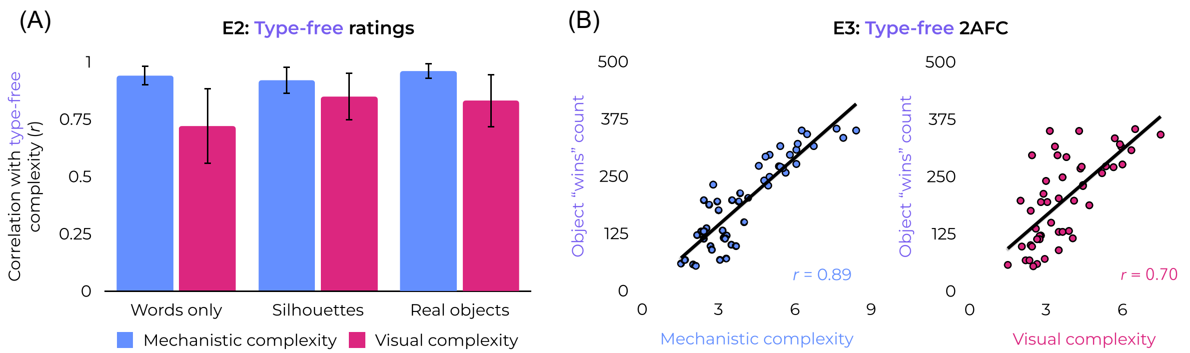
We converted these choices into ratings of object complexity by counting the number of "wins" for each object. In other words, the

[4] Though these differences in correlation coefficients are quite large, it is possible that only a few objects drive this difference and that it actually does not reflect a broad preference for mechanistic complexity. To address this, we performed a bootstrap simulation. Each simulation consisted of 1,000 iterations in which the objects included in the correlation were randomly sampled with replacement. In the words-only condition, all 1,000 iterations of the simulation resulted in a higher correlation coefficient for mechanistic complexity. In the silhouettes condition, mechanistic ratings had a higher correlation coefficient in 980/1,000 iterations, and in the real objects condition, mechanistic complexity was better correlated with type-free complexity in all 1,000 simulations once again. Thus, this effect pervades our entire stimulus set.

[5] Another way to compare the strength of these relationships is by placing both visual and mechanistic complexity into a linear regression that predicts type-free complexity. We can then compare the coefficients of each kind of complexity. We fit three models—one for each level of stimulus realism level. In all three, the coefficients of mechanistic complexity were significantly different from 0 (with $p < .001$ in each), as were the coefficients of visual complexity (although less so, with $p < .05$ in each). The coefficient of mechanistic complexity was significantly higher than that of visual complexity in the words-only and real object models ($p < .001$ in both) but not in the silhouettes model.

Figure 2

Results From Our Explicit Rating Tasks, in Which We Found a Preference for Mechanistic Complexity



Note. (A) In Experiment 2 (E2), participants rated the type-free complexity of objects from 1 to 9. We correlated these ratings with the ratings we gathered in Experiment 1 and found higher correlations between type-free complexity and mechanistic complexity than between type-free complexity and visual complexity in all three conditions. Error bars are 95% confidence intervals of the correlation coefficients. (B) In Experiment 3 (E3), participants performed a forced-choice task in which they said which of two objects was more complex. We counted the number of "wins" for each object and asked if wins were predicted by each kind of complexity. As before, we observed a higher correlation between mechanistic complexity and the number of object wins than between visual complexity and the number of object wins. 2AFC = two-alternative forced-choice. See the online article for the color version of this figure.

most complex object was the object that was chosen the most (i.e., had the most wins), and the least complex object was the object that was chosen the least (i.e., had the fewest wins). We correlated the number of wins here to the words-only ratings for mechanistic and visual complexity (as gathered in Experiment 1). Note that we also tested two more mathematically rigorous methods of ranking that account for opponent "strength" and number of "games" (Elo and a Bradley–Terry model). These more rigorous methods returned nearly identical results to our initial method, so we used the wins method for simplicity. (The results from all three methods are available in our OSF repository at https://osf.io/csfdq/.)

As in Experiments 1 and 2, trials with a response time below 200 ms were excluded; this excluded two trials total (out of 10,000). All 100 participants submitted a full data set, so zero participants were excluded.

Results

As before, we observed a preference for mechanistic complexity over visual complexity: mechanistic complexity $r(48) = 0.89$ versus visual complexity $r(48) = 0.70$ (both have $p < .001$; Figure 2B).[6,7] This experiment replicates the preference for mechanistic complexity from Experiment 2 in a new task. Arriving at similar results despite the difference in task and analysis (i.e., this task and analysis results in a generative ranking of objects, whereas the last one is simply a correlation between ratings) points to a consistent preference for mechanistic complexity in judging objects.

Experiment 4: Visual Search

Our previous two experiments show that mechanism is more important than appearance for judgments of object complexity. This is perhaps to be expected: Mechanistic complexity may be more important to our everyday lives (Rescher, 1998), and thus it may predict judgments more than visual complexity. However, might mechanistic complexity be so important that it is computed spontaneously, even when not strictly or explicitly required by a task?

Previous research shows that object complexity drives performance in a variety of implicit tasks where one does not need to judge complexity, such as visual search (Sun & Firestone, 2021). However, many of these works show the effect of visual complexity on implicit visual tasks. They relatively ignore mechanistic complexity, perhaps because one does not need to extract mechanistic complexity to complete such tasks. If mechanistic complexity is more important than visual complexity even in implicit visual tasks, that would provide additional evidence for the importance of mechanism.

Here, we adapted the visual search task in Sun and Firestone (2021). They found a "search asymmetry" (Wolfe, 2001) for visual complexity; participants were faster to find a visually complex target surrounded by visually simple distractors than vice versa, perhaps because complexity provides a signal that a visual object should be explored further. With this result, Sun and Firestone (2021) suggested that visual complexity is extracted automatically and modulates attention. Here, we ask if this result might apply to mechanistic complexity. In other words, does mechanistic complexity drive performance in a visual search task more than visual complexity?

We ask if participants display a search asymmetry for mechanistic complexity over visual complexity. This would be evidenced by faster response times to find a mechanistically complex, visually simple target surrounded by mechanistically simple, visually complex distractors than to find a visually complex, mechanistically simple target surrounded by visually simple, mechanistically complex

[6] Using the same bootstrap method as before, we observed higher r values for mechanistic complexity in 997/1,000 simulations, suggesting that this preference pervades the full range of objects.

[7] As before, we compared the regression coefficients of mechanistic and visual complexity for predicting the number of wins. The coefficient of mechanistic complexity was higher than that of visual complexity, and this difference was significant ($p < .001$). Note that both coefficients were significantly different from 0 ($p < .001$ for the mechanistic coefficient, $p < .05$ for the visual coefficient).

distractors (as in Sun & Firestone, 2021). Importantly, this design allows us to isolate the importance of mechanistic complexity. If participants were *only* computing visual complexity (and ignoring mechanistic complexity), then we would observe the same results as Sun and Firestone (2021)—a search asymmetry in the opposite direction of our prediction. However, observing a search asymmetry for mechanistic complexity over visual complexity suggests that mechanistic complexity may be being extracted and used in visual search. This would be especially striking, as one may expect visual complexity to drive performance more than mechanistic complexity in visual tasks.

Method

Participants

Two hundred new participants were recruited for this study. This sample was larger than our previous sample sizes and larger than the sample size in Sun and Firestone (2021) due to differences between our studies; our participants were recruited online (as opposed to their in-person participants) and completed fewer trials. Furthermore, we anticipated a more subtle effect than Sun and Firestone (2021); whereas they ask about an asymmetry between visually simple and visually complex objects, we ask for an asymmetry between two different *kinds* of complexity.

Stimuli and Procedure

Using our results from Experiment 1, we chose 10 objects with a high divergence in visual and mechanistic complexity—five objects with high mechanistic complexity and low visual complexity, and five objects with high visual complexity and low mechanistic complexity. The five mechanistically complex, visually simple objects were: phone, rocket, monitor, headphones, and tractor; the five visually complex, mechanistically simple objects were: tree, comb, backpack, shoe, and curtains.

On each trial, participants saw six objects appear as silhouette images in random positions (out of 16 possible positions in an invisible 4×4 grid) and had to say whether all the objects were the same or if one was different. Participants were told to respond as fast as they can. In line with the design in Sun and Firestone (2021), we had four trial types: mechanistic target (meaning that a random mechanistically complex object appeared alongside five of the same mechanistically simple distractors), visual target (the same as mechanistic target but with a visually complex object appearing alongside five visually simple distractors), all mechanistic (all six objects presented are mechanistically complex), and all visual (all six objects presented are visually complex). Participants completed 50 trials of each type (200 total) in a random order. The specific objects of each type appearing in each trial were chosen randomly, as was their position in the grid.

Stimuli were chosen in a contrasting way such that we could examine an asymmetry between the two kinds of complexity. For example, in the mechanistic target trials, a mechanistically complex object appeared alongside five mechanistically simple distractors. Because the objects chosen have high divergences in mechanistic and visual complexity, an alternative way to view the mechanistic target trials is that we presented a visually simple object alongside five visually complex distractors. However, if visual complexity alone was driving the results, we would observe the *opposite* asymmetry of the one we predict—as shown in Sun and Firestone (2021). This design ensured that an asymmetry for mechanistic target trials over visual target trials is in fact due to mechanistic complexity.

Note that we do not analyze the "all mechanistic" and "all visual" trials, as there is no asymmetry in those trials (and thus there is no effect to analyze). However, we still included these trials such that the number of all-same trials would equal the number of one—different trials. Also note, for example, that we do not present trials where a mechanistically complex target appears among different mechanistically complex distractors; this is because, as above (and like Sun & Firestone, 2021), we are seeking a search *asymmetry* between levels of complexity. Trials presenting target stimuli of the same level of complexity as the distractors would contain no asymmetry.

As per our preregistered analysis plans, we excluded participants who scored below 80% accuracy, and we excluded trials with a response time below 200 ms or above 2,000 ms. Six of 200 subjects did not submit a complete data set, and four additional subjects were excluded by the accuracy criteria (leaving 190 subjects total); 1,887 of the remaining 38,000 trials were excluded by our response time criteria. Our subsequent response-time analysis is done only on trials where participants responded correctly.

Results

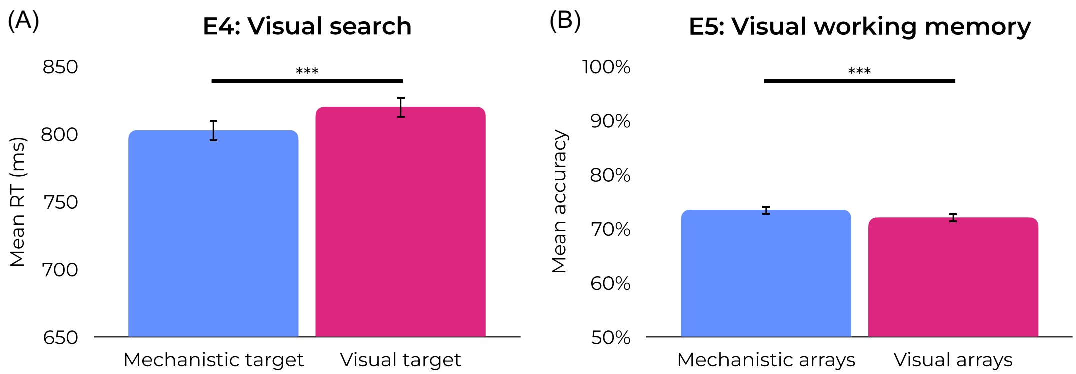
If mechanistic complexity drives behavior even in implicit, visual tasks, then we should observe a search asymmetry for it. This would be seen through faster response times for mechanistic target trials (where participants search for a mechanistically complex object surrounded by mechanistically simple distractors) than for visual target trials (where participants search for a visually complex object surrounded by visually simple distractors). And this is exactly what we observe: On mechanistic target trials, the mean subject response time was 803 ms, compared to 820 ms in the visual target trials, $t(189) = -4.38$, $p < .001$; 95% CI of differences [−24.93, −9.46]; $d = 0.32$; Figure 3A. Furthermore, this effect was not merely driven by a small subset of subjects; 117 of 190 subjects (62%) had numerically faster mean response times on mechanistic target trials than visual target trials, in line with the direction of our effect. Therefore, mechanistic complexity seems to drive performance more strongly than visual complexity in a visual search task. In other words, even in an implicit *visual* task (where one does not need to compute mechanistic complexity to perform the task), mechanistic complexity may matter more than visual complexity.[8]

It may have been expected for mechanistic complexity to be preferred over visual complexity for intuitive judgments. But here, we show that the mechanistic complexity may be more important than the visual complexity, even for visual search. Perhaps mechanistic complexity is so important to our everyday representations of object complexity that the mind extracts it automatically, even above more readily available visual information.

[8] Note that this does not contradict results from Sun and Firestone (2021), as their research question did not necessitate testing different kinds of complexity. Furthermore, they tested abstract shapes and blobs that had no "mechanism," and thus mechanistic complexity was not in the hypothesis space.

Figure 3

Results From Our Implicit Cognitive Tasks, in Which We Found That Mechanistic Complexity Drives Visual Attention and Visual Working Memory More Than Visual Complexity



Note. (A) Results from our visual search task in Experiment 4 (E4). Participants were faster to find a mechanistically complex object among mechanistically simple distractors ("mechanistic target") than they were to find a visually complex object among visually simple distractors ("visual target"; $p < .001$). (B) Results from our visual working memory task in Experiment 5 (E5). Participants were better at remembering arrays of mechanistically complex objects than arrays of visually complex objects ($p < .001$). Error bars show 95% confidence intervals for the difference between groups. RT = response time. See the online article for the color version of this figure.
*** $p < .001$.

Experiment 5: Visual Working Memory

Our results from Experiment 4 suggest that mechanistic complexity may affect performance in visual tasks previously thought to be affected only by visual complexity. To further show how mechanistic complexity drives implicit visual behaviors, we asked whether mechanistic complexity may also drive visual working memory. Are mechanistically complex objects easier to remember than visually complex ones?

To address this question, we took a similar approach to the one we took in Experiment 4: We adapted a well-established vision science paradigm that applies to visual complexity and asked whether it applies to mechanistic complexity. In Experiment 4, we did this with the visual search asymmetry from Sun and Firestone (2021; see Wolfe, 2001, for review on search asymmetries). Here, we do so with visual working memory, using our stimuli in the paradigm that Alvarez and Cavanagh (2004) employed to demonstrate how visual complexity affects visual working memory (see Bays & Husain, 2008, for a similar paradigm to probe visual working memory, and see Franconeri et al., 2013; Ma et al., 2014, for review). Specifically, Alvarez and Cavanagh (2004) found that visual working memory can store only a limited amount of visual "information" (here, visual complexity). In other words, more visually complex objects are harder to store in visual working memory; might a similar effect exist for mechanistic complexity?

Method

Participants

Three hundred new participants were recruited for this study. This is a large sample size because we anticipated a subtle effect. In much the same way that we expected to find more subtle visual search effects than what was found in Sun and Firestone (2021), so too did we expect to find more subtle visual working memory effects than what was found in Alvarez and Cavanagh (2004).

Stimuli and Procedure

Participants performed a memory task, as in Alvarez and Cavanagh (2004). On each trial, an array of five objects flashed for 500 ms at random positions in an invisible 3 × 3 grid. It was then masked for 900 ms before another array flashed for 500 ms. These are the same timing parameters as in Alvarez and Cavanagh (2004). Participants had to say whether the first array of objects was the same as the second array of objects or whether one object changed (using their keyboard, by clicking "S" for same and "D" for different). Thus, they had to quickly encode the array in their visual working memory.

Using our results from Experiment 1, we gathered the 10 objects with the largest positive difference between mechanistic and visual complexity (i.e., high mechanistic complexity, low visual complexity) and the 10 objects with the largest negative difference between the two kinds (i.e., low mechanistic complexity, high visual complexity). Note that these groups varied primarily in mechanistic complexity and not visual complexity (discussed in our Results section). Participants completed 200 trials, equally split between the following four types: "mechanistic same" (the five objects are chosen randomly from the high mechanistic, low visual complexity list; the initial and final arrays are the same), "visual same" (the five objects are chosen randomly from the low mechanistic, high visual complexity list; the initial and final arrays are the same), "mechanistic different" (the five objects are chosen randomly from the high mechanistic, low visual complexity list; the initial and final arrays differ by one randomly chosen object), and "visual different" (the five objects are chosen randomly from the low mechanistic, high visual complexity list; the initial and final arrays differ by one randomly chosen object). The order of the trials was randomized for each participant.

As per our preregistration, we excluded participants who scored below 50% accuracy (chance), and we excluded trials with a response time below 200 ms or above 5,000 ms. Twelve of 300 subjects did not submit a complete data set, and seven more subjects performed below-chance and were thus excluded by the accuracy criteria (leaving 281 subjects total). One thousand nine hundred seventy-six of the remaining 56,200 trials were excluded by our response time criteria.

Results

Participants were better at remembering arrays of mechanistically complex, visually simple objects (73.5% accuracy) than they were at remembering arrays of mechanistically simple, visually complex objects, 72.1% accuracy; $t(280) = 3.71$, $p < .001$; 95% CI of differences [0.67%, 2.17%]; $d = 0.22$. As in Experiment 4, this effect was not merely driven by a small subset of participants. In total, 167/281 (59%) of subjects had higher mean accuracy on mechanistic arrays than on visual arrays, in line with the direction of our effect. Furthermore, this effect cannot be explained by subjects only encoding visual complexity and ignoring mechanistic complexity. The mean visual complexity of the two groups of objects was not significantly different, 3.34 in the visually simple, mechanistically complex group versus 3.93 in the visually complex, mechanistically simple group; $t(17.9) = 1.08$, $p = .29$ in two-sample t test; meanwhile, the mean mechanistic complexity of the two groups differed significantly, 6.05 in the visually simple, mechanistically complex group versus 2.84 in the visually complex, mechanistically simple group; $t(16.0) = 6.26$, $p = .001$ in two-sample t test. In other words, the stimuli vary primarily in mechanistic complexity (and not visual complexity). Thus, mechanistic complexity is driving the effect.

Note that our effect goes in the opposite direction of the one observed for visual complexity in Alvarez and Cavanagh (2004). They found that visually complex objects are harder to store in visual working memory; we find that mechanistically complex objects are *easier* to store in visual working memory. Perhaps this is because of the importance of mechanism to our everyday lives (Rescher, 1998); it may be the case that information about the mechanistic complexity of an object is more useful than information about its visual complexity, making the former easier to encode and retrieve than the latter.

More broadly, our results from Experiments 4 and 5 show that borrowing classic tasks from vision science can help reveal implicit cognitive signatures of mechanistic complexity. Experiment 4 adapted a visual search asymmetry paradigm (from Sun & Firestone, 2021), and Experiment 5 adapted a visual working memory paradigm (from Alvarez & Cavanagh, 2004).

Transparency and Openness

All materials, code, and data are available on our OSF repository at https://osf.io/csfdq/. Interested readers may view our experiments—exactly as participants did—at https://perceptionstudies.github.io/mechanism. All experimental designs, analysis plans, and sample sizes were preregistered.

Discussion

Mechanistic complexity drives judgments, visual attention, and visual working memory more than visual complexity. First, we show that type-free ratings of complexity are better-correlated with mechanistic complexity than with visual complexity (Experiment 2); we replicate this finding with a 2AFC task (Experiment 3). Then, we use two different implicit tasks—a visual search task (Experiment 4) and a visual working memory task (Experiment 5)—to show that mechanistic complexity even drives visual behaviors (more than visual complexity). The results of the two visual tasks are especially striking, as representing mechanistic complexity is not required to complete a visual task. Additionally, one might think these cases are biased toward visual complexity given previous research that shows visual complexity can drive these processes. Our representations of object complexity therefore rely not only on the external appearances of objects but also on their inner workings—and may even rely on the latter more than the former. This finding is consistent with previous philosophical arguments about complexity (Rescher, 1998), developmental research about mechanism (Leslie, 1994), and common intuitions about objects (as in the car vs. bicycle example).

From Perceiving High-Level Objects to Perceiving High-Level Object Complexities

Our proposal that representations of object complexity rely on internal or higher level properties connects to previous work about the perception of objects more broadly. Foundational research shows that perception incorporates not only low-level features (e.g., color, shape) but also higher level properties such as causality, animacy, objecthood, and sophisticated relations between parts and objects (Heider & Simmel, 1944; Michotte, 1963; for review, see Hafri & Firestone, 2021; Scholl & Tremoulet, 2000). This reasoning parallels ours. Perceiving causality, animacy, and objecthood serves our immediate needs (and thus the visual system may not encode *only* low-level features); similarly, perceiving mechanistic complexity may serve our immediate needs (and thus the visual system does not represent *only* visual complexity). This may be why mechanistic complexity drives performance even in visual tasks.

Subsequent research on object representation has suggested that high-level properties may be as important as—if not more important than—low-level features. For example, center of mass (i.e., a higher level physical feature) predicts how people localize an object (by pointing) more than other, lower level properties (Boger & Ullman, 2023). This preference has also been explored extensively in development; 6-month-old infants encode conceptual category representations of objects even in the absence of perceptual features (Kibbe & Leslie, 2019; for review, see Kibbe, 2015).

This line of research may be useful in understanding how object complexity is represented in the mind. When we perceive the complexity of an object, perhaps we extract the complexity of not only its low-level visual features (i.e., as presented by contours, number of sides, and other proxies for visual complexity) but also its high-level features (i.e., as presented by its internal mechanism or number of functions). In this way, studying representations of complexity provides insight into how we represent objects more broadly.

Does Object Complexity Have a Default Kind?

At first, the notion of a "default" or "fundamental" kind of object complexity may seem odd. After all, we do not seem to have a "default" form of other cognitive judgments, such as beauty. However, within a specific domain, certain kinds of information seem to influence both explicit and implicit judgments. For example, symmetry seems to drive not only explicit attractiveness ratings (Rhodes et al., 1998) but also attention, and in ways that arise early in development (Bornstein et al., 1981; Rhodes et al., 1998). However, other kinds of facial beauty exist separate from symmetry. The "averageness" of a face may also be predictive of beauty and drive such implicit processes (Langlois & Roggman, 1990; Valentine et al., 2004). In the realm of faces (and perhaps visual patterns more broadly; Corballis & Beale, 1976), one may compare symmetry and averageness as two different "kinds" of beauty and ask which one wins out over the other in various tasks.

We propose an analogous understanding of object complexity. Within the domain of objects, we compare visual and mechanistic complexity as two "kinds" of complexity and ask which one wins out. We find that mechanistic complexity drives both explicit judgments and implicit visual processes. Both visual and mechanistic complexity are still important for representing object complexity, though, just as both symmetry and averageness are important for representing facial beauty. Future work may examine how other kinds of object complexity participate in our representations of object complexity. For example, functional complexity (the complexity of the functions an object can do; Ahl & Keil, 2017) may also be very useful to our everyday lives. Might it show similar signatures to mechanistic complexity? Or might it prove to be a separate piece of the puzzle of object complexity?

Concluding Remarks

Representing mechanistic complexity serves many purposes in our everyday lives. It is perhaps unsurprising, then, that judgments of object complexity are more aligned with mechanistic complexity than with visual complexity. We show that mechanistic complexity not only predicts direct judgments but also drives implicit visual behaviors. Consequently, representations of complexity may rely on mechanistic information more than visual information.

Constraints on Generality

Subjects in our experiments were recruited via Prolific (for a discussion of this subject pool, see Peer et al., 2017). The studies were open only to U.S. adults. We do not take it for granted that our findings generalize beyond this group. However, given the simple nature of our questions in Experiments 1–3 and the implicit nature of our response metrics in Experiments 4 and 5, we feel it is possible our results will extend to other populations.

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