

**Visual explanations prioritize functional properties at the expense of visual fidelity**

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All experimental materials, study preregistrations, data, and analysis code are publicly available in our GitHub repository: [https://github.com/cogtoolslab/causaldraw\\_public2021](https://github.com/cogtoolslab/causaldraw_public2021).

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**Abstract**

Visual explanations play an integral role in communicating mechanistic knowledge about how things work. What do people think distinguishes such pictures from those that are intended to convey how things look? To explore this question, we used a drawing paradigm to elicit both visual explanations and depictions of novel machine-like objects, then conducted a detailed analysis of the semantic information conveyed in each drawing. We found that visual explanations placed greater emphasis on parts of the machines that move or interact to produce an effect, while visual depictions emphasized parts that were visually salient, even if they were static. Moreover, we found that these differences in visual emphasis impacted what information naive viewers could extract from these drawings: explanations made it easier to infer which action was needed to operate the machine, but more difficult to identify which machine it represented. Taken together, our findings suggest that people spontaneously prioritize functional information when producing visual explanations but that this strategy may be double-edged, facilitating inferences about physical mechanism at the expense of preserving visual fidelity.

*Keywords:* natural pedagogy, causal learning, explanation, visual production

**Visual explanations prioritize functional properties at the expense of visual fidelity**

From infants exploring the objects in their immediate environment to scientists exploring the frontiers of our solar system, humans are driven to understand how things work and use that knowledge to generate desired outcomes. However, acquiring such mechanistic knowledge from firsthand experience can often be costly in time and effort (Lagnado & Sloman, 2004; Steyvers et al., 2003) and thus the majority of our knowledge about the world depends on its faithful transmission from one generation to another (Boyd et al., 2011; Csibra & Gergely, 2009). This knowledge transmission has long been supported by mechanistic explanations, which help to expose causal relationships latent in otherwise fleeting and complex information (Keil & Lockhart, 2021).

What characterizes good mechanistic explanations, and how do they relate to the phenomena they are intended to explain? Prominent theoretical perspectives highlight several hallmark features (Bechtel, 2011; Wimsatt, 1976), noting that effective mechanistic explanations decompose a causal system into its interacting parts and specify the causal relationships between those parts in the context of a particular function. For example, a bicycle functions by transferring power from the movement of the pedals to the drive wheel via the roller chain between the two wheels, propelling the entire bicycle forward. Such an explanation can be distinguished from a merely descriptive report (e.g., “a bicycle has two wheels, pedals, and a chain), which does not specify the causal relationship between the interacting parts (Corriveau & Kurkul, 2014), and from a teleological explanation (e.g., “a bicycle is for riding from one location to another), which does not decompose the causal system into any constituent parts nor specify how they interact (Kelemen & Rosset, 2009). In addition to playing a key role in scientific theories (Bechtel, 2009), there is growing evidence that mechanistic explanations are also privileged in people’s intuitive understanding of artifacts and biological entities (Chuey et al., 2020; Lockhart et al., 2019). Nevertheless, our understanding of what intuitions people have about what information to prioritize when producing mechanistic explanations themselves is less well developed. Initial insights may be gleaned from prior work investigating the content of explanations that people

produce while studying a physical system, which has documented the inclusion of abstract principles (Chi & VanLehn, 1991) and the notion that some explanations may prioritize outward appearance while others emphasize internal properties (Walker et al., 2014; Walker et al., 2017). However, these analyses have generally lacked the resolution to tease apart different hypotheses concerning how people weigh these different kinds of information when constructing a coherent explanation.

While the majority of prior studies investigating explanation behavior have focused on verbal explanations (Chi & VanLehn, 1991; Legare & Lombrozo, 2014; Lombrozo, 2016; Walker et al., 2014; Walker et al., 2017), explanatory *visualizations* may be especially useful for probing the cognitive processes engaged during the communication of mechanistic knowledge (Hegarty, 2011; Mayer, 1999; Scaife & Rogers, 1996; Tversky, 2005). Visualizations naturally exploit shape-based and spatial cues to expose both the relevant part-based and relational abstractions that underlie mechanistic understanding (Forbus et al., 2011; Hegarty & Just, 1993; Hegarty et al., 2003; Tversky, 2001), as well as how these abstractions map back onto physical parts of the target system (Bobek & Tversky, 2016; Fan, 2015; Gobert & Clement, 1999; Newcombe, 2013). Moreover, there is ample evidence that visualizations can facilitate learning and inference as by comparison with text alone (Glenberg & Langston, 1992; Hegarty & Just, 1993; Larkin & Simon, 1987; Mayer, 1989) by leveraging a small set of relational symbols, such as lines and arrows (Heiser & Tversky, 2006; Tversky, 2005; Tversky et al., 2002; Tversky et al., 2000). However, previous studies that have elicited visual explanations of mechanistic phenomena have not included the detailed analyses of their content that would be required to understand what distinguishes visual explanations in people's minds from other types of visualizations. In particular, while prior work has found that visualizations prompted by functional descriptions of a physical system contain more arrows than those cued by structural ones (Heiser & Tversky, 2006), it remains unclear whether these symbols were simply added to an otherwise ordinary illustration, or whether they formed part of a distinct type of visualization emphasizing information in a substantially different way.

The current studies aim to overcome key limitations of prior work by conducting a thorough investigation of what information people prioritize when generating mechanistic explanations, and leveraging the distinctive properties of *visual* explanations to gain insight into how explanatory abstractions are grounded in our direct experience with mechanical systems. In Experiment 1, we measure how much people emphasize information about visual appearance or physical mechanisms when producing explanatory drawings of novel mechanical objects, as opposed to depictive illustrations. In Experiment 2, we measure how well naive viewers can map such information back to the corresponding source object. Together, data from these two experiments help to distinguish two potential hypotheses concerning how people generate visual explanations. Under the *cumulative* hypothesis, people first produce a complete depiction of an object's parts, after which they augment this representation with symbols that convey how these parts interact. Under the *dissociable* hypothesis, people intending to communicate mechanistic knowledge refrain from drawing all the parts of the object, instead emphasizing the most relevant ones and how they interact, rather than preserving information about the object's overall appearance. Overall, our results were more consistent with the latter dissociable hypothesis: explanatory drawings emphasized different parts from depictions and more effectively communicated mechanistically relevant information to naive viewers, while less effectively conveying information about an object's visual appearance. Together, these findings suggest that people engaging in visual explanation spontaneously prioritize functional information at the expense of visual fidelity.

### **Experiment 1A: Production of visual explanations and depictions**

Our first goal was to identify the semantic properties that characterize visual explanations of mechanistic knowledge. To accomplish this, we developed a web-based drawing platform in which participants were presented with a series of novel machines and asked to produce two kinds of drawings: on *explanation* trials, they were prompted to produce visual explanations to help a naive viewer learn how the machine functioned; on *depiction* trials, they were prompted to

produce visual depictions to help a naive viewer identify the machine by its appearance. To identify the properties that are distinctive of visual explanations, we use depictions as a baseline for comparison, which were produced in the absence of any explicit goal to communicate causal information about the machines. We chose drawing in our visual production task because it is a basic visualization technique that requires minimal equipment (i.e., any stylus and surface), but is a versatile and accessible technique for communicating information in visual form (Sayim & Cavanagh, 2011). Additionally, people have a robust ability to interpret drawings, despite the fact that drawings produced by novices may omit many details and distort the size and proportion of represented objects (Eitz et al., 2012; Fan et al., 2018).

## Method

### Participants

50 participants (29 male; mean age = 39.1 years) were recruited from Amazon Mechanical Turk for the visual production experiment. Two additional participants were recruited, but their data were not included in the study for not meeting our predefined exclusion criteria (e.g., the drawings consisted of scribbles or were otherwise uninterpretable). In this and all subsequent experiments, participants provided informed consent in accordance with the UC San Diego IRB.

### Stimuli

We designed 6 novel machines composed from simple mechanical parts (i.e., gears, levers, pulleys). There were two machines employing each type of part. Half of the mechanical parts in each machine were *causal*, meaning they could be used to produce a desired effect (i.e., turn on a light bulb attached to each machine); the other half of mechanical parts were *non-causal*. To match how visually salient they were, the causal and non-causal parts within each machine were always of the same type (e.g., gear), and were approximately matched in size and number (Fig. 2, left). For each machine, we produced a video demonstration of it in which a demonstrator's hand was shown to interact with both the causal and non-causal mechanical parts

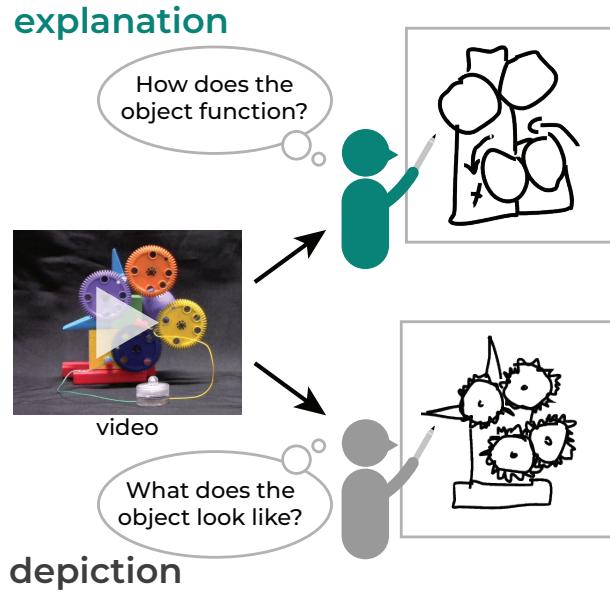
twice each, in a counterbalanced order, to show that the causal part reliably turned on the light, whereas the non-causal part did not. The order of manipulation was counterbalanced across all machines for a total of 12 video demonstrations. Each video was 30 seconds, and the duration of time in which the researcher manipulated each causal and non-causal part was controlled for through post-production video editing. We also conducted a separate validation study to ensure that participants could generally determine how the machines could be operated to activate the light bulb based on these video demonstrations (see Supplementary Materials).

## Procedure

We presented a naive group of participants with a series of 6 videos (one of each machine). After each video finished playing, participants were cued to produce one of two kinds of drawings: on *explanation* trials, they were prompted to produce visual explanations intended to help a naive viewer learn how the machine could be operated to activate a light bulb; on baseline *depiction* trials, they were prompted to produce visual depictions intended to help a naive viewer identify the machine by its appearance (Fig. 1). All participants produced three visual explanations and three visual depictions, in a randomized sequence, such that they drew one of each type of drawing for each type of machine. Participants used their cursor to draw in black ink on a digital canvas embedded in their web browser (canvas = 500 x 500px; stroke width = 5px). Each stroke was rendered in real time on the participant's screen as they drew and could not be deleted once drawn. Participants were not limited in amount of time that they could spend drawing in each trial. At the beginning of each session, participants also completed two practice trials to familiarize themselves with the drawing interface.

## Results & Discussion

The resulting dataset contained 300 drawings from 50 unique participants: 150 visual explanations and 150 depictions (Fig. 2). Insofar as participants are predicted to include more information in visual explanations in accordance with the *cumulative hypothesis*, we predicted that visual explanations would contain more visual detail and take more time to produce, relative



**Figure 1**

**Study 1: Visual Production Task.** On each trial, participants viewed a 30-second video demonstrating how to operate a machine to turn on a light bulb. On half of the trials, after the video finished playing, participants were then prompted to produce an explanatory drawing. On the other half of the trials, they were prompted to produce a depictive drawing.

to visual depictions. On the other hand, if participants invest a similar amount of effort in both conditions but differ in their semantic content as predicted by the *dissociable hypothesis*, we predicted that the two types of drawings would not substantially differ in how detailed they were nor how much time they took to be produced. To distinguish these possibilities, we analyzed the number of strokes and total drawing time using a linear mixed-effects model predicting the number of strokes from condition and included random intercepts for the type of machine (e.g., gear, lever, pulley) and individual participant.

We found that participants used a similar number of strokes (explanation: 20.33; depiction: 18.9;  $b = 1.44$ ,  $t = 1.04$ ,  $p = 0.301$ ; Fig. 1B, left) and amount of time drawing in both conditions (explanation: 59300ms; depiction: 57689ms;  $b = 1144.75$ ,  $t = 0.359$ ,  $p = 0.72$ ), suggesting that participants had invested a similar degree of effort when producing both types of

drawings. However, while these results provide preliminary evidence against the *cumulative* hypothesis, they also indicate that such simple effort-based measures are insufficient to capture differences in the *semantic information* conveyed by each type of drawing.

machines	ROIs	depiction				explanation			

### **Experiment 1B: Characterizing semantic content in visual explanations and depictions**

To go beyond these effort-based measures, we next crowdsourced annotations from a separate group of naive participant in order to systematically characterize the *semantic information* contained in these drawings. We used these annotations in two ways: first, to understand which parts of the machine participants in Experiment 1A had thought relevant to include in their drawing; and second, to quantify the degree to which each drawing faithfully preserved the relative size and location of each part. One possibility is that visual explanations focus on causally relevant parts, but still faithfully preserve their visual properties. Alternatively, they may distort their visual properties, for example, by making these causally relevant parts more visually salient in their drawing. To distinguish these possibilities, we leveraged techniques from computer vision to precisely measure the differences in the apparent size and location of each drawn part and its actual size and location in the target machine.

## **Method**

### **Participants**

252 participants (210 male;  $M_{age} = 38.9$  years) were recruited from Amazon Mechanical Turk to provide semantic annotations of the drawings produced in Experiment 1A. We excluded data from 28 additional participants, who did not meet our preregistered inclusion criteria (i.e., low accuracy on attention-check trials, response time <5s).

### **Task Procedure**

Annotators were presented with a set of 10 drawings that were randomly sampled from those drawn in the visual production experiment, as well as reference color photographs of the original machines. In these photographs, each part was color-coded and assigned a unique label and numerical identifier (e.g., ‘Gear 2’). Annotators were asked to tag each pen stroke in the drawing based on which part they thought it represented. If a stroke depicted a symbol (e.g., arrow, motion line) rather than a physical part of the machine, annotators were asked to

additionally label which part(s) the symbol referred to. If a stroke's meaning was not clear, they could select an "I don't know" option instead. Annotators also completed one attention-check trial that used a drawing from the Experiment 1A dataset that was particularly straightforward to parse and had been manually segmented by the authors. If annotators made 3 or more errors when labeling strokes in the attention-check drawing, all data from that session were excluded from subsequent analysis.

### Preprocessing annotation data

For each stroke in every drawing, we obtained labels from at least three annotators indicating which part of the machine it corresponded to (e.g., "gear", "lever", "structural"). Each of these labels were then further grouped into higher-level semantic categories: *causal* strokes representing mechanical parts that were causally related to turning on the light bulb, *non-causal* strokes representing mechanical parts that were not causally related to turning on the light bulb, *structural* strokes representing structural parts, and *symbolic* strokes, including arrows and other marks indicating motion and interactions between parts.

We found that 64.9% of strokes received the same label by all three annotators, and 95.0% of strokes received the same label by at least two of the three annotators. 5.0% of strokes did not reach a majority consensus and received more annotations to resolve this conflict. Moreover, within visual explanations, 55.5% of strokes received the same label by all three annotators, and 93.2% of strokes received the same label by at least two of the three annotators. Within depictions, 75.0% of strokes in depictions received the same label by all three annotators, and 96.9% of strokes received the same label by at least two of the three annotators. In subsequent analyses, we collapsed across annotators and assigned the modal label to strokes which had been given the same label by at least two annotators. For the remaining strokes that did not receive a modal label, we randomly sampled an annotation from the set of annotations that had been assigned to it. We also excluded 5 drawings from subsequent analyses that were deemed to be entirely uninterpretable.

### Spatial error analysis

To evaluate how accurately the drawings preserved information about the location and size of each part, we used the following procedure. First, to compute the size and location of drawn parts, we grouped all strokes within a drawing that were tagged with the same semantic label, then determined the coordinates of the rectangular bounding box containing those parts (Fig. 3B). For example, if a drawing contained strokes representing four different gears and some structural parts, then this step would yield five bounding boxes, one for each gear, and the fifth containing all structural parts. Strokes representing symbols and/or the light bulb were excluded from analysis. Next, to compute the size and location of target parts, we color-coded each part of the still images of the machines in Adobe Photoshop and grouped all the pixels of the same color. We then calculated the coordinates of the individual bounding boxes for each part. Because the goal of our analysis was to measure how accurately drawings preserved relative size and location information, we aligned each drawing to its target machine before computing size and location errors. Specifically, we calculated the overall bounding box containing all strokes and the overall bounding box of the target machine containing all parts and then applied the translation and scaling transformations needed to align the two.

To calculate raw location error for a given part, we computed the Euclidean distance between the centroid of the bounding box for each drawn part and the centroid of the bounding box for the target part. The raw location error for the drawing as a whole was computed by taking the mean of these distances across all parts that appeared in the drawing. We then divided this raw location error by the length of the diagonal of the machine's bounding box to derive a normalized measure of location error, enabling more straightforward aggregation of location error estimates between machines of different sizes. Additionally, to calculate raw size error for a given part, we calculated the difference in area between the bounding box of the drawn part and the bounding box for the target part. We then normalized this raw size error by dividing it by the area of the target part, such that values larger than 1 indicated that the part appeared larger in the drawing than its referent in the still image, and values smaller than 1 indicated that the part appeared

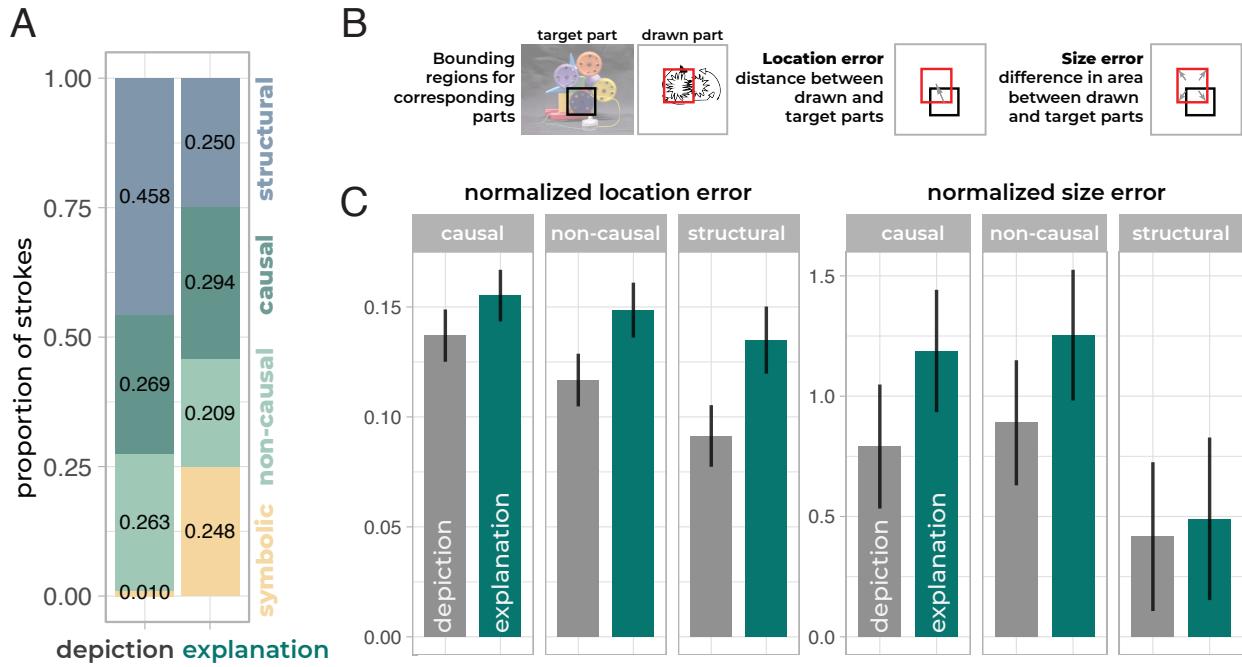
smaller in the drawing than its referent. The normalized size error for a drawing as a whole was computed by taking the mean across all parts that appeared in the drawing.

## Results & Discussion

Insofar as visual explanations place a greater emphasis on functional information than depictions do in accordance with the *dissociable hypothesis*, we hypothesized that visual explanations would contain: (1) more strokes representing causally relevant parts and (2) more symbols (e.g., arrows) representing movement and interactions between parts. To evaluate the first hypothesis, we constructed a linear mixed-effects model predicting the number of strokes labeled as “causal” from condition and included random intercepts for individual drawing and individual participant. To evaluate the second hypothesis, we constructed a linear mixed-effects model predicting the number of strokes labeled as “symbol” from condition and included random intercepts for the type of machine (e.g., gear, lever, pulley) and individual participant.

We found that among strokes representing a mechanical part (i.e., gear, lever, or pulley), a greater proportion were devoted to representing causal parts in visual explanations than in depictions (explanation: 58.0%, depiction: 42.0%,  $b = 0.382$ ,  $z = 3.44$ ,  $p = 5.9e - 4$ ; Fig. 3A). Moreover, visual explanations contained more strokes that represented symbols (explanation: 24.8%, depiction: 1.0%,  $b = 2.48$ ,  $t = 1.392$ ,  $p = 1.67e - 1$ ) and fewer strokes representing structural parts (explanation: 25.0%, depiction: 45.8%,  $b = -2.77$ ,  $t = -4.86$ ,  $p = 1.31e - 5$ ). These results suggest that the goal of communicating mechanistic knowledge leads people to produce drawings that place greater emphasis on causally relevant components and how they move, and less emphasis on static components, even if they are visually salient.

Insofar as visual explanations exaggerate the appearance of important parts of each machine, we hypothesized that they would not preserve information about their relative sizes and locations as accurately as visual depictions do. To evaluate this hypothesis, we fit a linear mixed-effects model predicting the size and location error from condition, including random intercepts of individual machine and participant. We found that mechanical parts were



**Figure 3**

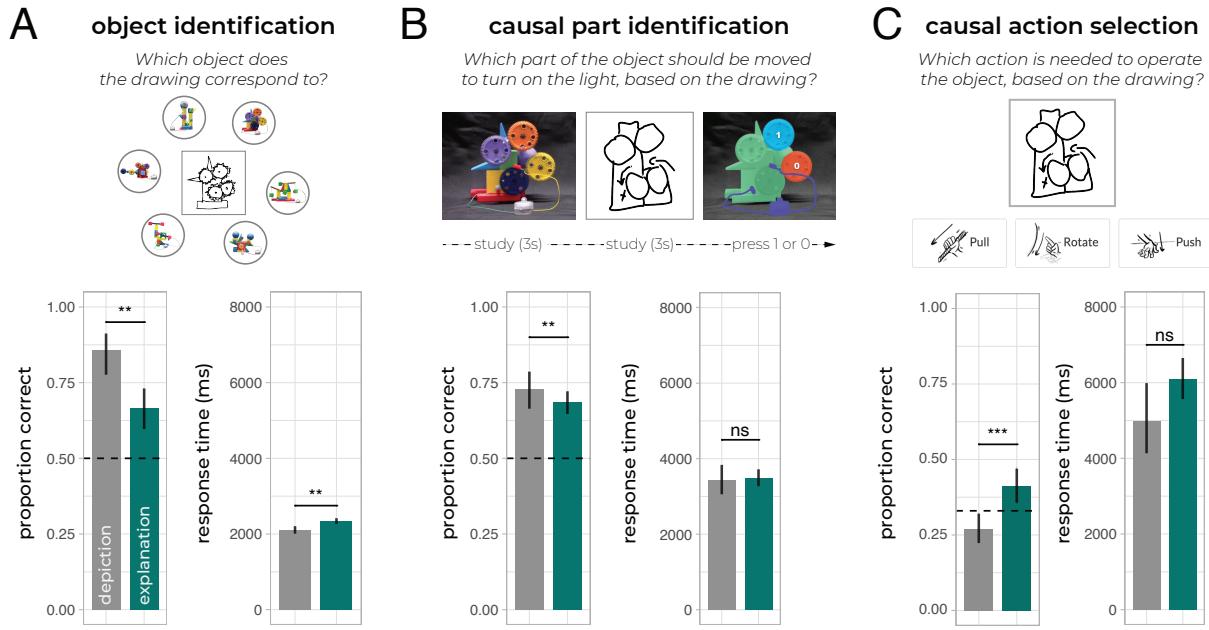
**Study 1: Results.** **A:** Proportion of strokes conveying different semantic information: causal strokes representing mechanical parts that turned the light on; non-causal strokes representing mechanical parts that did not; structural strokes representing static parts; and symbolic strokes, including arrows and other marks indicating motion and interactions between parts. **B:** Accuracy of spatial information in drawings was estimated by defining bounding regions for corresponding parts in each drawing and video, then computing the difference in size and location between the drawn and target parts. **C:** Normalized location and size errors for different semantic part categories. Normalized location errors reflect relative differences between the target and drawn parts, rescaled by the size of the machine. Normalized size errors reflect relative differences between the target and drawn parts, rescaled by the size of the target part. Error bars represent 95% CIs.

consistently drawn larger in visual explanations than in depictions (explanation: 72.4px, depiction: 60.8px,  $b = 8.41$ ,  $t = 1.97$ ,  $p = 0.0496$ ), in addition to being drawn somewhat further from their actual locations, relative to other parts of the machine (explanation: 75.1px, depiction: 62.3px,  $b = 11.6$ ,  $t = 3.15$ ,  $p = 0.18e - 2$ ; Fig. 3C). These findings are consistent with the notion that when explaining how a machine functions, people distort the appearance of functionally relevant parts to make them more salient and discount the importance of preserving exact spatial relationships. Taken together, Experiments 1A and 1B provide evidence that having the goal of communicating mechanistic knowledge systematically affects the kind of information people prioritize when producing visual explanations.

### Experiment 2A: Object identification

However, a critical test of how *useful* such communicative strategies are can be measured how well other people can interpret these drawings to achieve their own behavioral goals. In Experiment 2, we recruited three additional cohorts of naive participants to view the drawings made in the visual production experiment (Experiment 1A) and measured how well each drawing supported their ability to identify the original machine (Experiment 2A), to infer which part of the machine to intervene on to operate it (Experiment 2B), or to infer which action was needed to operate the machine to activate the light (Experiment 2C).

In Experiment 2A, we hypothesized that the reduced emphasis on structural parts (i.e., ‘background’) in visual explanations would make it harder to match it to the original machine, relative to visual depictions. To test this hypothesis, we designed a visual search task to probe how quickly and accurately naive viewers could identify the machine that corresponded to each drawing.

**Figure 4**

**Study 2: Visual Inference Tasks and Results.** **A:** In Study 2A, participants identified the machine that matched each drawing. **B:** In Study 2B, participants identified which part of the machine they should intervene on to turn on the light bulb. **C:** In Study 2C, participants inferred which action they would need to perform to turn on the light. Error bars represent 95% CIs.

## Method

### Participants

50 participants (24 male;  $M_{age} = 20.5$  years) were recruited from the UC San Diego study pool. Two additional participants were recruited, but data from their sessions were excluded for technical problems (i.e., inability to click on images).

### Task Procedure

Each participant was presented with all 300 drawings from Experiment 1A in a randomized sequence. At the beginning of each trial, participants moved their cursor to a crosshair displayed at the center of an empty display. When ready, participants clicked this

crosshair to reveal a single drawing (175 x 175px) at that location, surrounded by a circular array of six color photographs (125px x 100px, radius = 250px), one of each machine (Fig. 4A). The angular distance between each photo was constant (i.e., 60 degrees) and their angular locations were randomized between trials. Participants were instructed to click on the machine that the drawing corresponded to as quickly and accurately as possible. At the beginning of the session, participants completed 6 practice trials where they were cued with *photos* of each machine (instead of drawings), and had to click on the matching photo in the array.

## Results & Discussion

To investigate how well these drawings support participants' ability to identify the machines, we fit a null model predicting identification accuracy that included random intercepts for different production participants. Although there were 6 machines, we defined chance-level performance at 50%, a theoretical upper bound reflecting our expectation that confusions would be most likely to arise between machines of the same type (e.g., gears).

To evaluate our hypothesis that participants would be slower when presented with visual explanations relative to when they were presented depictions, we fit a linear mixed-effects model predicting response time from condition, as well as additional predictors controlling for the number of each type of stroke within a drawing (i.e., causal, non-causal, structural, symbol), the interaction between condition and the number of each type of stroke, and random intercepts for individual drawings and participant. Additionally, to evaluate our hypothesis that participants would be less accurate when viewing visual explanations rather than depictions, we fit a mixed-effects logistic regression model to predict individual trial outcomes, with the same fixed and random effects structure as our response-time model above.

We found that participants were reliably above chance performance for both types of drawings (explanation:  $b = 0.561, z = 3.94, p = 8.16e - 5$ ; depiction:  $b = 1.28, z = 10.1, p = 2e - 16$ ; Fig. 4A). Consistent with our primary hypothesis, we found that participants were both slower (correct trials only: explanation: 2646ms; depiction: 2339ms;  $b = 1.02e - 1, t = 3.26, p =$

$1.29e - 3$ ; Fig. 4A) and less accurate when cued with a visual explanation than with a depiction (explanation: 62.4%; depiction: 76.7%;  $b = -0.899$ ,  $z = -2.89$ ,  $p = 3.75e - 3$ ; Fig. 4B, left).

These results suggest that our manipulation of communicative goals in Experiment 1A measurably impacted how well viewers could extract relevant information from each type of drawing, such that depictive drawings were more informative about the identity of the target machine.

### Experiment 2B: Causal part identification

How well do visual explanations support naive viewers' ability to identify which part of the machines to intervene on to produce desired goals? In Experiment 2B, we hypothesized that greater emphasis on functional parts, especially those that were causally relevant, would make it easier for learners to infer which component to intervene on to activate the light bulb. To test this hypothesis, we designed another visual search task that probed how quickly and accurately naive viewers could locate the causally relevant part when provided with a drawing of the machine.

### Method

#### Participants

297 participants (100 male;  $M_{age} = 28.4$  years) were recruited from Prolific (N=99) and the study participant pool at UCSD (N=198). 8 additional participants were recruited but data from their sessions were excluded, for technical problems with displaying the experimental stimuli (e.g., the videos did not load). We used a larger sample size in Experiment 2B to collect approximately the same number of observations per drawing as we had collected in Experiment 2A.

#### Task Procedure

Participants were presented with a randomly sampled set of 6 drawings from Experiment 1A, one of each machine, in a randomized sequence. On every trial, participants were presented

with three images laid out in a horizontal array, appearing in succession: first, a color photograph of one of the machines appeared on the left; second, after a 3-second delay, a drawing of it appeared in the middle; and third, after another 3-second delay, another photograph of the same machine appeared on the right, this time with one causal part and one non-causal part highlighted in different colors (Fig. 4B). Participants were instructed to press a key (i.e., either 0 or 1) to indicate which of the highlighted parts they would intervene on to turn on the light, and to do so as quickly and accurately as possible. At the beginning of the session, participants completed a series of practice trials in which they were familiarized with the task interface.

## Results & Discussion

As in Experiment 2A, we fit a null model predicting identification accuracy that included random intercepts for different production participants to evaluate the degree to which participants performed above chance. To evaluate whether participants would be faster in identifying the causal part when presented with a visual explanation rather than a depiction, we constructed a linear mixed-effects model to predict response time from condition, as well as additional predictors controlling for the number of each type of stroke within a drawing (i.e., causal, non-causal, structural, symbol) and the interaction between condition and the number of each type of stroke, and random intercepts for individual drawings and participant. Additionally, to evaluate our hypothesis that participants would be more accurate for explanations than depictions, we fit responses with the same statistical model as in Experiment 2A.

We found that both types of drawings supported above-chance performance (explanation:  $b = 0.849, t = 10.53, p < 2e - 16$ ; depiction:  $b = 0.919, z = 13.04, p < 2e - 16$ ; Fig. 4B), suggesting that both types of drawings carried meaningful signal about the identity of the causally relevant parts. However, we did not find evidence for an advantage for explanatory drawings: on correct trials, participants took a similar amount of time to make their response (explanation: 3488ms; depiction: 3424ms,  $b = -1.971e - 2, t = -0.287, p = 0.775$ ; Fig. 4B). If anything, participants were *less* accurate when cued with a visual explanation than with a depiction (explanation:

68.5%; depiction: 72.3%,  $b = -0.516$ ,  $z = -2.601$ ,  $p = 0.929e - 2$ ; Fig. 4B). Taken together, these results show that the greater visual emphasis on causal parts in explanatory drawings did not necessarily translate to improved ability to identify these parts *in situ*. Rather, they suggest that there may be more to the construction of an effective visual explanation than displaying the most functionally important entities more prominently.

### Experiment 2C: Causal action selection

While the prior experiment evaluated how well visual explanations supported naive viewers' ability to identify *where* to intervene on the machines, here we evaluated how well these drawings could support participants' ability to infer *how* to intervene on the machines. In other words, how well do visual explanations support naive viewers' ability to infer which action is needed to successfully operate the machines? Similar to Experiment 2B, we hypothesized in Experiment 2C that greater emphasis on functional parts, especially those that were causally relevant, would make it easier to infer which action was necessary to intervene on the machines to activate the light bulb. To test this hypothesis, we developed a task probing how quickly and accurately naive viewers could identify the appropriate action to perform when provided with a drawing of each machine.

## Method

### Participants

267 participants (75 male;  $M_{age} = 21.3$  years) were recruited from the UC San Diego study pool. Three additional participants were recruited, but data from their sessions were excluded for technical problems (i.e., videos did not load).

### Task Procedure

Participants were presented with a random set of 6 drawings from Experiment 1A, one of each machine, in randomized sequence. On each trial, participants were presented with a single

drawing, under which there were 3 buttons labeled as "Pull", "Push", "Rotate" and "I don't know" (Fig. 4C). Participants were instructed to click the button that corresponded to the action needed to operate the machine, based on their interpretation of the drawing, and were told to prioritize accuracy. At the beginning of the session, participants completed a series of practice trials in which they were familiarized with the task interface.

## Results & Discussion

To evaluate the degree to which participants performed the task above chance, we fit a null model predicting accurate responses that was identical in structure to that used in Study 2A and 2B. Next, to evaluate differences in how quickly participants could identify the correct action, we fit a linear mixed-effects model predicting response time from condition, as well as additional predictors controlling for the number of each type of stroke within a drawing (i.e., causal, non-causal, structural, symbolic), the interaction between condition and the number of each type of stroke, and random intercepts for individual drawings and participants. Additionally, to evaluate differences in how accurately participants could identify the correct action, we fit their responses using the same type of statistical model as in Experiment 2A and 2B, with two simplifying modifications: because visual explanations consistently contained more strokes illustrating symbols than depictions, we removed the predictor for number of strokes corresponding to symbols, as well as the interaction between condition.

Surprisingly, neither visual explanations nor depictions supported performance above chance (chance = 33%; explanation:  $b = -0.29$ ,  $z = -2.98$ ,  $p = 2.87e - 3$ ; depiction:  $b = -1.023$ ,  $z = -9.72$ ,  $p = 2e - 16$ ; Fig. 4C). We found that participants more accurately identified the correct action when cued with a visual explanation (explanation: 41.5%; depiction: 26.8%,  $b = 0.662$ ,  $z = 3.72$ ,  $p = 2.01e - 4$ ; Fig. 4C). Between conditions, they took a similar amount of time to make their response (correct trials only, explanation: 6085ms; depiction: 4975ms,  $b = 0.0887$ ,  $t = 0.691$ ,  $p = 0.4904$ ; Fig. 4C), suggesting that the greater accuracy was unlikely to be due to a speed-accuracy tradeoff. Taken together with the results of Study 2B, these findings suggest that

explanatory drawings better supported naive viewers' ability to figure out which action was needed to interact with the machine, even if they did not help them identify which part of the machine to interact with. More broadly, these results show that the visual differences between visual explanations and depictions that we measured in Experiment 1 lead to specific and dissociable consequences on the kind of information people can easily extract from them (e.g., object identity about what the object looks like vs. procedural knowledge about what type of action to use to successfully interact with the object).

## General Discussion

Explanatory visualizations are a crucial tool for encoding mechanistic knowledge, a key goal of scientific reasoning and communication. Nevertheless, we do not yet understand what ordinary people think is relevant when trying to explain how something works, as well as how these visual explanations guide people towards appropriate inferences. Towards closing this gap, we investigated what information people prioritize when drawing visual explanations of simple mechanical objects, and measured how well these explanations enabled other people to learn about these objects based on their drawings alone. We found that people spontaneously emphasized functionally important parts of these objects when producing an explanation, using more strokes to draw these parts and making them appear larger than when they only aimed to produce a visually accurate drawing of the object. They also drew abstract symbols, including arrows and motion lines, suggesting that they believe that providing an explanation means going beyond drawing physical components of the same object. While these explanatory drawings succeeded in communicating to other people which action was needed to interact with the object, they did not necessarily make it easier to connect key parts in the drawing to key parts of the object itself. Taken together, our findings show that ordinary people display sensitivity to information about functional organization (i.e., how parts move and interact) when asked to produce a visual explanation, in a way that systematically trades off with information about structural organization (i.e., what parts look like and where they are).

Our findings contribute to a growing body of work characterizing explanatory preferences (Lombrozo, 2016) and the cognitive consequences of producing explanations (Bobek & Tversky, 2016; Chi et al., 1994; Fiorella & Zhang, 2018; Legare & Lombrozo, 2014; Walker et al., 2014; Walker et al., 2017). In particular, participants who performed our visual explanation task prioritized causally relevant information at the expense of other salient information. This tendency is broadly consistent with previous evidence that individuals who are prompted to produce verbal explanations tend to privilege more abstract, functional properties over salient, perceptual features (Legare & Lombrozo, 2014; Walker et al., 2014). However, rather than focusing on what is learned by the individuals producing the explanations, the current studies examined how the balance of structural and functional information in visual explanations guide inferences made by downstream learners. We found that the explanatory drawings elicited in our study supported certain inferences to a greater degree than others, suggesting that explanations are not necessarily superior to depictions in all settings, but rather a specific tool for conveying knowledge cast at a particular level of abstraction.

Our experimental approach also enables follow-up studies that probe how different kinds of communicative goals may subtly impact the kind of information people believe to be important to include in their explanations. In our study, participants were cued to produce drawings explaining how the machines functioned to produce the desired effect. However, participants may have interpreted these instructions to mean that they should either: (a) explain the specific mechanisms that cause the desired effect for this machine (i.e., how *these* gears turn the light on) or (b) explain the general principles governing the class of mechanisms used by the machine (i.e., how gears work in general). A participant approaching the task with the latter interpretation may be expected to produce drawings that departed more substantially from the visual appearance of the machine than a participant equipped with the former interpretation. Such drawings may be less effective for helping a naive viewer understand any specific machine, but potentially more effective for helping them generalize to a wide variety of machines employing similar physical mechanisms. Future studies could test these predictions directly, shedding light on how the

tradeoff between functional and structural information may be modulated by how general a visual explanation is intended to be.

Another key direction for future work is to examine how expertise influences visual explanation behavior. The participants in our studies were unlikely to have received specific training in how to design effective visual explanations, and thus it may not be surprising that the explanations they produced did not outperform depictions in supporting identification of causally relevant parts. One potential explanation for this finding is that, by frequently omitting other (non-causal) mechanical parts and structural parts, these explanations failed to provide enough contextual information to help viewers situate the causally relevant part relative to the rest of the object. Future work could test this hypothesis by prompting drawers to take the perspective of a naive viewer (Shafto et al., 2014), to examine whether they would be more likely to include enough additional structural information to produce more informative visual explanations. Such evaluations may help to clarify the role of perspective taking and pedagogical expertise in the production of explanations that are effective for different audiences.

Overall, advancing our understanding of how visual explanations communicate mechanistic knowledge may have broad implications for psychological theories of explanatory behavior, as well as for the role of visualizations in scientific learning and pedagogy.

### **Author contributions**

H. Huey, C. M. Walker, and J. E. Fan developed the study concept and design. Testing and data collection were performed by H. Huey and J. E. Fan. H. Huey performed the data analysis of Experiment 1A, 1B, 2A, 2B, and 2C under the supervision of J. E. Fan, and X. Lu performed the spatial analyses of Experiment 1B under the supervision of J. E. Fan. H. Huey drafted the manuscript, and C. M. Walker, and J. E. Fan provided critical revisions. All authors approved the final version of the manuscript.

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