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\textbf{ABSTRACT}

Young children often endorse explanations of the natural world that appeal to functions or purpose—for example, that rocks are pointy so animals can scratch on them. By contrast, most Western-educated adults reject such explanations. What accounts for this change? We investigated 4- to 5-year-old children’s ability to generalize the form of an explanation from examples by presenting them with novel teleological explanations, novel mechanistic explanations, or no explanations for 5 nonliving natural objects. We then asked children to explain novel instances of the same objects and novel kinds of objects. We found that children were able to learn and generalize explanations of both types, suggesting an ability to draw generalizations over the form of an explanation. We also found that teleological and mechanistic explanations were learned and generalized equally well, suggesting that if a domain-general teleological bias exists, it does not manifest as a bias in learning or generalization.

The popular children’s book \textit{Look Look!} concludes by telling its young readers, “[S]tars shine all for you” (Linenthal, 1998, p. 22). While Western adults might balk at this purposive take on the nonliving natural world, it is not foreign to most young children. In fact, given the choice between explaining why objects like rocks are pointy by appealing to a purpose (e.g., “so that animals . . . could scratch on them”) or by appealing to a mechanical process (e.g., “because little bits of stuff piled up on top of one another over a long time”), most elementary school students opted for the former (Kelemen, 1999d; see also Piaget, 1929; Sully, 1900). With age and education, however, this tendency becomes more selective (e.g., Casler & Kelemen, 2008; Kelemen, 1999b). For most Western adults, “teleological” or “functional” explanations—explanations that appeal to a purpose, function, or goal—are restricted to artifacts and some biological traits (Lombrozo & Carey, 2006). So, while most will accept that streetlights shine “for us,” they will not say the same about stars.

Why do children’s teleological preferences change during the course of development? Previous work has convincingly shown that culture and education play important roles. For example, by 6 years of age, secular Israeli children showed a weaker and more circumscribed preference for teleological explanations than did orthodox Israeli children (Diesendruck & Haber, 2009; see also Casler & Kelemen, 2008; Kelemen, 2003). There is
also evidence that adults with greater exposure to Western education are more selective in their application of teleological explanations (Casler & Kelemen, 2008; Sánchez Tapia et al., 2016) and that baseline teleological tendencies may be attenuated in a more secular culture (Rottman et al., 2017). Moreover, culture can affect the content of teleological explanations: A study comparing Quechua-speaking Peruvians to Americans revealed that the former group produced more teleological explanations involving ecological relationships (Sánchez Tapia et al., 2016; see also Ojalheto, Waxman, & Medin, 2013). These findings indicate that there must be some mechanism(s) by which exposure to particular cultural or pedagogical materials, practices, or contexts affects the perceived scope of teleological explanations.

One possibility is that as children hear particular explanations, they form generalizations concerning the kind of explanation involved (i.e., teleological or mechanistic) and the kind of entity to which it is being applied (e.g., an artifact or a nonliving natural thing). For example, after hearing many mechanistic explanations for nonliving natural things (e.g., those mountains resulted from volcanic activity, the rain results from condensation), children could form the generalization that nonliving natural things tend to support mechanistic explanations. But the prerequisites to this kind of generalization are not trivial: Children must be able to represent kinds of explanations as such and group objects into classes that have some correspondence to explanation type. In fact, the single previous study that tested an intervention to teach children to produce mechanistic explanations did not succeed in doing so: Kelemen (1999d, 2003) included training to teach children to select mechanistic explanations over teleological alternatives by providing them with an example of how a scientist would explain cloud formation (e.g., clouds “are all made up of tiny drops of water and sometimes when the water drops get really cold then it rains,” Kelemen, 2003, p. 207). This training had very little effect on subsequent explanations, with most children endorsing teleological explanations for most items.

In the current study, we aimed to investigate whether children can successfully generalize an explanation type from one case to another by implementing a training regimen that might be a better match to children’s everyday experience. Rather than providing a single example with instructions to answer “like a scientist,” we presented children with multiple explanations of a particular type, and we then assessed their learning and generalization. Specifically, we introduced 4- and 5-year-old children to five examples of nonliving natural objects (e.g., stars) from a fictional planet, Bizorm. Each object was introduced with no explanation (e.g., “Wow, look at this!”), with a teleological explanation (e.g., “Stars on Bizorm are very bright yellow so that people can see them”) or with a mechanistic explanation (e.g., “Gas burns in the stars on Bizorm, so they are very bright yellow”). We then solicited explanations from children in two tasks: a learning test and a transfer test. In the learning test, we assessed how effectively the provided explanations were remembered and applied by asking children to explain novel instances of the same kinds of objects (e.g., another star). In the transfer test, we asked children to explain the properties of nonliving objects or phenomena that were not previously seen (e.g., a river).

The transfer test was especially crucial for assessing whether the type of explanation modeled in training generalized to novel items. Specifically, we could see whether the children in the teleological training condition generated more teleological explanations on the transfer test than did children in the neutral condition (who received no training) and
whether the children in the mechanistic training condition generated more mechanistic explanations on the transfer test than did children in the neutral condition. In both cases, it was important to consider children’s responses relative to the neutral condition, rather than in absolute terms, to ensure that preferences for one explanation type over the other were driven by the training itself and not by the explanatory preferences children might have had concerning those items even in the absence of training.

By testing children’s learning and transfer for both mechanistic and teleological explanations, our experiment also had the potential to shed light on ongoing debates about the scope of teleological thinking. According to one perspective, teleology reflects a “default” and domain-general preference to reason about the world in terms of purpose (e.g., Kelemen, 1999a, 1999c; Kelemen, Rottman, & Seston, 2013). This perspective is supported by evidence that children accept teleological explanations across domains (Kelemen, 1999d) and that this preference is not a simple consequence of parental input (Kelemen, Callanan, Casler, & Pérez-Granados, 2005). Moreover, adults err in the direction of accepting scientifically unwarranted teleological explanations when responding under time pressure (Kelemen & Rosset, 2009; Kelemen et al., 2013) or when cognitively impaired (Lombrozo, Kelemen, & Zaitchik, 2007), suggesting that a preference for teleological explanations could persist as a default preference throughout the life span.

An alternative perspective is that teleological explanations reflect a more selective “design stance” that is restricted to reasoning about the products of intentional or apparent design—namely, artifacts and biological adaptations (Keil, 1992, 1994). Supporting this view, Greif, Kemler-Nelson, Keil, and Gutierrez (2006) found that children sometimes asked function-seeking questions for artifacts (e.g., “What is it for?”), but they never did so for animals. It is also worth noting that while children have tended to accept teleological explanations for animals and for nonliving natural things when they are offered, this tendency is not indiscriminate. For example, Kelemen (1999d) found that even second graders were more ambivalent about social teleological explanations (e.g., “[T]hey had long necks so that they could hold up their friends when they got tired swimming”) than they were about self-serving teleological explanations (e.g., “[T]hey had long necks so that they could grab at fish and feed on them”), and they found that teleological explanations were more often favored for living objects than for nonliving natural objects, such as rocks, ponds, and sand. Similarly, while adults accepted some scientifically unwarranted teleological explanations under speeded conditions (e.g., “[E] arthworms tunnel underground to aerate the soil”), they did not accept teleological explanations that were treated as “bad” control items (e.g., “[C]ars have horns to illuminate dark roads”; Kelemen & Rosset, 2009). These findings suggest some selectivity in the scope of teleological explanations.

Given these ongoing debates, a secondary goal of the present research was to revisit questions about the scope of teleological explanations using our novel method. Instead of focusing on which explanations children produced (e.g., Sánchez Tapia et al., 2016) or selected (e.g., Kelemen, 1999d) or focusing on the function-seeking questions children ask (Greif et al., 2006), we focused on how readily children learned and generalized novel explanations when they were offered. If children favor teleological explanations as a cognitive default, we might expect it to manifest as a learning bias, with teleological explanations more readily learned and generalized than mechanistic explanations. In contrast, if children show some early selectivity, we might expect mechanistic explanations
to be more readily learned and generalized in our task, given that the domain of nonliving natural objects does not typically involve actual or apparent design. By focusing on a domain with a contested role for teleology, our method thus provides a new way to address long-standing questions about the selectivity of children’s teleological preferences.

In sum, our experiment investigated how young children learn and generalize teleological and mechanistic explanations by presenting them with no explanations, with novel teleological explanations, or with novel mechanistic explanations and then soliciting explanations for matched and novel cases. Our study is among the first to consider whether children can form generalizations over explanation types, effectively extending a mode of explanation from trained instances to novel cases. Our study can not only shed light on the nature of explanation (Keil, 2006; Lombrozo, 2006, 2012, 2016), but it can also inform ongoing debates about the scope of young children's teleological preference.

Methods

Participants

Sixty children (M<sub>age</sub> = 4;6; range = 3;11–5;11) were recruited from local preschools (N = 58) or a science museum (N = 2) and were randomly assigned to one of three conditions: neutral baseline, teleological training, or mechanistic training. There were 20 children in each condition, with no significant differences in age, F(2, 57) = 1.362, p = .264. One additional child was replaced due to experimenter error. The children represented a range of ethnicities.

Materials

A picture book was used in training and included five drawings of nonliving natural objects (pond, mountain, cave, island, star). The learning test for this book included an additional five drawings of these objects, modified to be similar but distinguishable. The transfer task used drawings of five new natural objects or phenomena (desert, canyon, thunder, river, volcano). Sample illustrations are provided in Figure 1. (All stimuli can be found in online supplemental materials.) The majority of these items and properties were drawn from stimuli used in previous research (e.g., Kelemen, 1999d).

Procedure

Training task. Children were introduced to the five-page training book with drawings of nonliving natural objects from the planet “Bizorm” (see Figure 1, top). A statement accompanied each drawing (see Table 1). In the neutral baseline condition, the experimenter provided a neutral statement (e.g., “Wow, look at this!”). In the teleological training condition, the experimenter provided a teleological explanation (e.g., “Caves on Bizorm are very dark so that animals can hide in them.”). In the mechanistic training condition, the experimenter provided a mechanistic explanation (e.g., “There are no holes for light to shine through in caves on Bizorm, so they are very dark.”).
Figure 1. Sample stimuli from the picture books used in training (top; pointy mountain and bright stars), in the learning test (middle; pointy mountain and bright star), and in the transfer test (bottom; hot desert and steaming volcano).

Table 1. Statements that accompanied each of the five items in the training task for each condition, along with the corresponding question that was later asked on the learning test.

<table>
<thead>
<tr>
<th>Item</th>
<th>Neutral Baseline</th>
<th>Teleological Training</th>
<th>Mechanistic Training</th>
<th>Test question</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pond</td>
<td>“Wow, look at this!”</td>
<td>“Ponds on Bizorm are very still so that the water doesn’t spill out.”</td>
<td>“No rocks fall into ponds on Bizorm, so they are very still.”</td>
<td>“Why do you think this pond is so still?”</td>
</tr>
<tr>
<td>Cave</td>
<td>“Wow, look at this!”</td>
<td>“Caves on Bizorm are very dark so that animals can hide in them.”</td>
<td>“There are no holes for light to shine through in caves on Bizorm, so they are very dark.”</td>
<td>“Why do you think this cave is so dark?”</td>
</tr>
<tr>
<td>Star</td>
<td>“Wow, look at this!”</td>
<td>“Stars on Bizorm are very bright yellow so that people can see them.”</td>
<td>“Gas burns in the stars on Bizorm, so they are very bright yellow.”</td>
<td>“Why do you think this star is so bright yellow?”</td>
</tr>
<tr>
<td>Mountain</td>
<td>“Wow, look at this!”</td>
<td>“Mountains on Bizorm are very pointy so that animals don’t climb on them.”</td>
<td>“Mountains on Bizorm are very pointy because smooth pieces of mountain fall off.”</td>
<td>“Why do you think this mountain is so pointy?”</td>
</tr>
<tr>
<td>Island</td>
<td>“Wow, look at this!”</td>
<td>“Islands on Bizorm are very small so that ships don’t bump into them.”</td>
<td>“Islands on Bizorm are very small because the ocean covers most of the land.”</td>
<td>“Why do you think this island is so small?”</td>
</tr>
</tbody>
</table>
Learning test. After observing all training items, children received the learning test (see Figure 1, middle). The original drawings remained visible as the experimenter introduced five new drawings (e.g., “Here is another cave from the planet Bizorm.”). Children were then asked why each property held for the objects in the new drawings (e.g., “Why do you think this cave is so dark?”). Children were first prompted to provide a free response. After the free response, they were presented with a forced-response option that included the explanations provided during the teleological and mechanistic training conditions, with order varied within children and counterbalanced across children.

Transfer test. Children were shown five drawings of nonliving natural objects or phenomena from planet Earth (see Figure 1, bottom). As with the learning test, children were prompted to explain a property of each item and were then given a forced-choice option between teleological and mechanistic explanations, with order varied within children and counterbalanced across children (see Table 2).

Explanation coding and preliminary analyses

Free-response coding. Free-response explanations were coded into three nonoverlapping categories (see Table 3 for examples): “teleological” (appealing to a function or purpose, N = 110 of 600); “mechanistic” (appealing to proximate causal processes, N = 234 of 600); or “other” (N = 256 of 600). Within the class of “other” explanations, 2 involved no response from the child at all, 26 were “I don’t know,” and 15 were another statement of ignorance (such as “no idea” or “no guesses”). The remaining 213 responses were often repetitions of the property in question (what Baum, Danovitch, and Keil [2008] classified as a circular explanation, and what Frazier, Gelman, and Wellman [2009] classified as “restatement”), or they were descriptions of the picture (what Frazier et al. [2009] classified as “descriptive”). Eighty percent of children’s responses were coded by both the first and third authors; kappa was .70. The analyses reported here correspond to those of the first author, who coded all responses.

The authors coded explanations while masked to condition. To accomplish this and for consistency across conditions, we coded explanations as “teleological” or “mechanistic” irrespective of whether the explanation matched the one that was offered in training.

Table 2. Complete set of items for the transfer test, including the teleological and mechanistic explanations provided for the forced-choice question.

<table>
<thead>
<tr>
<th>Item</th>
<th>Question</th>
<th>Teleological</th>
<th>Mechanistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desert</td>
<td>“Why do you think this desert is so hot?”</td>
<td>“[Or] do you think it’s so that people don’t walk on it?”</td>
<td>“[Or] do you think it’s because there are no trees to shade it?”</td>
</tr>
<tr>
<td>River</td>
<td>“Why do you think this river is so narrow?”</td>
<td>“[Or] do you think it’s so that animals can cross over it?”</td>
<td>“[Or] do you think it’s because not very much water goes through it?”</td>
</tr>
<tr>
<td>Thunder</td>
<td>“Why do you think this thunder is so loud?”</td>
<td>“[Or] do you think it’s so that people know to go inside?”</td>
<td>“[Or] do you think it’s because lightning in the clouds makes a noise?”</td>
</tr>
<tr>
<td>Canyon</td>
<td>“Why do you think this canyon is so deep?”</td>
<td>“[Or] do you think it’s so that things on this side can’t cross over to the other side?”</td>
<td>“[Or] do you think it’s because little pieces fell away over a long time?”</td>
</tr>
<tr>
<td>Volcano</td>
<td>“Why do you think this volcano has steam on top?”</td>
<td>“[Or] do you think it’s so that people know to stay away from it?”</td>
<td>“[Or] do you think it’s because the hot lava heated up the inside of the volcano?”</td>
</tr>
</tbody>
</table>
However, participants overwhelmingly generated explanations that did match those offered in training—only 7 responses in the teleological training condition and 2 in the mechanistic training condition (out of 200 responses) were teleological or mechanistic explanations that differed from those offered. Moreover, the explanations that were produced in these cases were often related to the explanations originally provided. For example, one child trained to believe that caves are dark so that animals can hide in them offered the free response that they are dark “so they can sleep in there,” and a child taught that stars are bright so that people can see them explained that stars are bright “so people can see in the dark.” These infrequent departures from trained explanations did not suggest any problems with one particular item type or explanation being more memorable or plausible than another.

**Forced-choice coding.** For the forced-choice responses, we summed the number of teleological explanations chosen for the learning and transfer tests. Overall, participants chose teleological explanations on 2.58 of the 5 learning trials ($SD = 1.44$, range $= 0–5$) and on 2.42 of the of the 5 transfer trials ($SD = 1.06$, range $= 0–5$), neither of which was significantly different from chance, $t(59) = 0.448$, $p = .656$, and $t(59) = -0.608$, $p = .546$ (one-sample $t$ tests). Moreover, a mixed analysis of variance with condition as a between-subjects factor, test type (learning, transfer) as a within-subjects factor, and the mean number of teleological responses as the dependent variable revealed that forced-choice responses did not differ as a function of condition, $F(2, 57) = 2.133$, $p = .128$.1

Responses on the forced-choice question may have been near chance for a methodological reason. The forced-choice question was posed to all children, even those who had provided a free response that matched one of the options provided. It is possible that this follow-up prompted children to change their answers (Bonawitz, Shafto, Yu, Bridgers, & Gonzalez, 2018; Gonzalez, Shafto, Bonawitz, & Gopnik, 2012). In fact, during the 10 trials for which a forced-choice option followed a free response, children changed their explanation from mechanistic to teleological or teleological to mechanistic an average of 2.57

1Other results from this analysis were a nonsignificant effect of test type, $F(1, 57) = 0.623$, $p = .433$, and a nonsignificant interaction, $F(2, 57) = 0.324$, $p = .725$. 

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**Table 3.** Explanation coding categories along with sample responses for three items.

<table>
<thead>
<tr>
<th>Coding Category</th>
<th>Question</th>
<th>Teleological</th>
<th>Mechanistic</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>‘Why do you think this cave is so dark?’</strong></td>
<td>“So animals can hide in it.”</td>
<td>“Because the light can’t shine because the hole’s so small.”</td>
<td>“Cause that’s how caves are.”</td>
<td>“Cause that’s how caves are.”</td>
</tr>
<tr>
<td> </td>
<td>“Maybe it’s dark so that the animals can hide and the people can find the animals.”</td>
<td>“There are no holes for light to shine through.”</td>
<td>“Because it looks like a shadow.”</td>
<td></td>
</tr>
<tr>
<td><strong>‘Why do you think this thunder is so loud?’</strong></td>
<td>“So all the people can hear it.”</td>
<td>“Because it’s electricity.”</td>
<td>“Because that’s what thunder does.”</td>
<td></td>
</tr>
<tr>
<td> </td>
<td>“So people can hear it.”</td>
<td>“Cause thunder is loud and rain is quiet, but when you mix them together it makes it really loud.”</td>
<td>“Because when there’s a rainstorm, there’s thunder.”</td>
<td></td>
</tr>
<tr>
<td><strong>‘Why do you think this canyon is so deep?’</strong></td>
<td>“Because it’s so there’s lots of room for people to walk.”</td>
<td>“Because you dig it so deep.”</td>
<td>“Because that’s how canyons are.”</td>
<td>“Because the canyons are really tall.”</td>
</tr>
</tbody>
</table>
times ($SD = 1.741$, range $= 0–7$). Given this methodological concern and children’s chance responding, we restricted subsequent analyses to the free-response data.

**Results**

We were interested in two main questions pertaining to children’s learning of the explanations and their generalizations. First, how readily did children learn the particular teleological or mechanistic explanations provided during training (as reflected by the learning test), and did children learn one type of explanation more readily than the other? Second, how readily did children generalize the modeled explanation type to novel items (as reflected by the transfer test), and did children generalize one type of explanation more readily than the other? We address these questions in turn.

To address the first question, we analyzed free responses on the learning task as a function of condition (see Figure 2). Children produced an average of $1.22$ ($SD = 1.805$, range $= 0–5$) teleological explanations, and this number varied as a function of condition, $F(2, 57) = 45.567, p < .001, \eta^2_p = .615$. Children produced $3.20$ ($SD = 1.795$) teleological explanations in the teleological condition, $0.30$ ($SD = 0.657$) in the neutral condition, and $0.15$ ($SD = 0.489$) in the mechanistic condition. Post-hoc Tukey tests revealed that responses in the teleological condition differed significantly from the other two conditions ($p < .001$), which did not differ from each other ($p = .909$).

Because the distribution of teleological responses was skewed toward 0 in the mechanistic and neutral conditions, we also conducted a nonparametric independent-samples Kruskal-Wallis test, which confirmed that the distribution of responses differed as a function of condition ($p < .001$). Comparing pairs of conditions with independent-samples Mann-Whitney U tests similarly confirmed that the teleological condition differed significantly from the mechanistic and neutral conditions ($ps < .001$), which did not differ from each other ($p = .602$).

Children produced an average of $1.30$ mechanistic explanations ($SD = 1.660$, range $= 0–5$) on the learning test, and this number also varied as a function of condition, $F(2, 57) = 34.635, p < .001, \eta^2_p = .549$. Children produced $0.20$ ($SD = 0.410$) mechanistic

![Figure 2](image_url). The mean number of teleological and mechanistic explanations offered (of five) on the learning test as a function of training condition. Error bars correspond to one standard error of the mean in each direction.
explanations in the teleological condition, 0.70 (SD = 1.174) in the neutral condition, and 3.00 (SD = 1.522) in the mechanistic condition. Post-hoc Tukey tests revealed that responses in the mechanistic condition differed significantly from the other two conditions (p < .001), which did not differ from each other (p = .351).

Once again, the distribution of mechanistic responses was skewed toward 0 in the teleological and neutral conditions. We thus conducted a nonparametric independent-samples Kruskal-Wallis test, which confirmed that the distribution of responses differed as a function of condition (p < .001). Comparing pairs of conditions with independent-samples Mann-Whitney U tests similarly confirmed that the mechanistic condition differed significantly from the teleological and neutral conditions (ps < .001), which did not differ from each other (p = .314).

We next considered whether teleological and mechanistic explanations were learned differentially. To do so, we first coded responses in the teleological and mechanistic conditions as training-consistent (i.e., teleological explanations produced in the teleological training condition were coded as matches, and mechanistic explanations produced in the mechanistic training condition were coded as matches). Simply comparing the proportion of matches across conditions, however, could reflect differences in the test items related to their bias for teleological versus mechanistic explanations and not differential effects of learning as a function of the training. We therefore treated responses in the neutral condition as an indication of how “teleologically biased” or “mechanistically biased” the items were, and we used these responses as a baseline correction for the teleological and mechanistic training conditions. Specifically, we subtracted the mean number of teleological explanations produced on learning items in the neutral condition (i.e., 0.30) from each teleological match score in the teleological condition, and we subtracted the mean number of mechanistic explanations produced in the neutral condition (i.e., 0.70) from each mechanistic match score in the mechanistic condition.

Having computed these baseline-corrected match scores, which reflect the extent to which a training condition increased the rate of training-consistent responses over the neutral condition, we used an independent-samples t test to compare the rate of training-consistent responses produced in the teleological versus mechanistic conditions. The result was not significant (teleological, $M = 2.900, SD = 1.795$; mechanistic, $M = 2.300, SD = 1.522$), $t(38) = -1.140, p = .261$. Addressing our first question, then, these results suggest that children were able to effectively learn some of the explanations provided during training but that teleological and mechanistic explanations were learned equally readily.

To address our second question, we analyzed free responses on the transfer task as a function of condition (see Figure 3). Children produced an average of 0.62 (SD = 1.106, range = 0–5) teleological explanations, and this number varied as a function of condition, but only marginally, $F(2, 57) = 2.459, p = .095, \eta^2_p = .079$. Children produced 1.05 (SD = 1.395) teleological explanations in the teleological condition, 0.35 (SD = 0.489) in the neutral condition, and 0.45 (SD = 1.146) in the mechanistic condition. Post-hoc Tukey tests revealed that no two conditions differed significantly (ps > .10). Because responses in all conditions were skewed toward 0, we also conducted a nonparametric independent-samples Kruskal-Wallis test, which similarly did not show a significant effect of condition (p = .126).

For mechanistic explanations, children produced an average of 2.60 (SD = 1.392, range = 0–5) such responses, and this number varied as a function of condition, $F(2, 57) = 6.333, p = .003, \eta^2_p = .182$. Children produced 2.00 (SD = 1.214) mechanistic
explanations in the teleological condition, 2.40 \( (SD = 1.392) \) in the neutral condition, and 3.40 \( (SD = 1.231) \) in the mechanistic condition. Post-hoc Tukey tests revealed that responses in the mechanistic condition differed significantly from responses in the other two conditions \( (p < .05) \), which did not differ from each other \( (p = .588) \). While responses were normally distributed, we followed up with nonparametric tests, which mirrored these patterns of significance.

To evaluate whether teleological and mechanistic explanations were generalized differentially, we again coded the number of training-consistent responses produced in the teleological and mechanistic training conditions and subtracted the mean number of responses of the corresponding type from the neutral condition to serve as a baseline correction. An independent-samples \( t \) test comparing these difference scores was not significant (teleological, \( M = 0.700, SD = 1.395 \); mechanistic, \( M = 1.000, SD = 1.231 \)), \( t(38) = 0.721, p = .475 \). Addressing our second question, then, these results suggest that children were able to generalize the explanation type learned during training (at least for mechanistic explanations) but that teleological and mechanistic explanations were generalized equally readily.

**General discussion**

Our findings suggest that when it comes to nonliving natural objects, such as stars and caves, 4- to 5-year-old children are able to learn novel teleological and mechanistic explanations and to generalize these kinds of explanations to novel items. Moreover, they are able to learn and generalize these two explanation types equally well. We now consider possible interpretations and implications of our results.

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2It is worth noting that mechanistic responses were more common in the transfer test than in the learning test. We expect that this finding reflects idiosyncratic properties of our stimulus materials, but it is also possible that participating in the learning test itself induced children to respond more mechanistically or that the shift from Planet Bizorm to Earth had some impact.
Our primary research question concerned the mechanism(s) by which children’s explanatory preferences change during the course of development. Given that culture and education are both factors, it is plausible that children are able to generalize from individual explanations that they encounter, and thus come to learn which kinds of explanations apply to particular kinds of cases. Our findings suggest that children are indeed able to generalize in this way, with several examples of a particular explanation type sufficient for them to generate completely novel explanations of that same type. We speculate that our training was successful, while the training from Kelemen (1999d, 2003) was not successful, because we provided children with multiple examples rather than a single case. From these examples, children were able to extract the common explanatory form despite variation in content, suggesting some representation of explanation type with respect to which they could note similarities.

Our findings did not reveal the precise nature of the generalization that children drew. For example, it is possible that they generalized over the syntactic structure of the modeled explanations, over a more abstract representation of explanation type, or over properties of items’ causal histories (Kelemen & DiYanni, 2005; Lombrozo & Carey, 2006). Although many possibilities remain open, we think it is unlikely that children followed a low-level strategy based on particular words or isolated cues. If they were picking up on repeated words, for example, we would expect more robust generalization in the teleological training condition, where all modeled teleological explanations had the form “P so that F,” compared with the mechanistic training condition, where the explanations varied in construction. Instead, we found significant generalization in the mechanistic training condition and a marginal trend in the teleological training condition.

Our secondary research question concerned whether teleological and mechanistic explanations might be learned or generalized differentially. We did not find such effects. This finding is noteworthy because the domain of nonliving natural objects is a contested case, which some believe falls within the scope of teleology (e.g., Kelemen, 1999b) and some believe falls outside of it (e.g., Greif et al., 2006). With that said, our null result should be interpreted with caution. Research on cultural evolution suggests that even small biases can generate large differences over time (e.g., Kalish, Griffiths, & Lewandowsky, 2007) and influence the nature of culturally accepted beliefs (Boyer, 2001; Boyer & Ramble, 2001). So even if children start out with a very weak bias favoring one type of explanation over the other, this bias could manifest as a strong preference later in development or later in the course of cultural evolution.

Our study has several limitations. Given the known effects of age, culture, and education on explanatory preferences, findings from a single sample should be generalized with caution. Our study was also restricted to a small number of items from the domain of nonliving natural things. Future work should investigate a wider range of items and domains and in so doing explore children’s ability to draw generalizations not only over kinds of explanations, but also over appropriate kinds of entities. Such work should also investigate individual differences across children.

In sum, we found that children were able to learn and to generalize novel teleological and mechanistic explanations and did so equally well for both types of explanations. This finding demonstrates that children are able to form generalizations over types of explanations, which is likely to be one of the core mechanisms by which explanatory preferences change throughout the life span. So, while young children may occasionally hear that stars “shine all for you,” subsequently encountering a preponderance of mechanistic
explanations could be enough to curb children’s teleological tendencies toward the natural world as they mature.

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