



When and how children use explanations to guide generalizations

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ABSTRACT

Explanations highlight inductively rich relationships that support further generalizations: if a knife is sharp *because it is for cutting*, we can infer that other things for cutting might also be sharp. Do children see explanations as good guides to generalization? We asked 108 4- to 7-year-old children to evaluate mechanistic, functional, and categorical explanations of object properties, and to generalize those properties to novel objects on the basis of shared mechanisms, functions, or category membership. Children were significantly more likely to generalize when the explanation they had received matched the subsequent basis for generalization (e.g., generalizing on the basis of a shared mechanism after hearing a mechanistic explanation). This effect appeared to be driven by older children. Explanation-to-generalization coordination also appeared to vary across relationships, mirroring the development of corresponding explanatory preferences. These findings fill an important gap in our understanding of how explanations guide young children's generalization and learning.

1. Introduction

A fidget spinner is an object with a ball bearing that allows it to spin with the flick of a finger, with the goal of helping the user to relieve nervous energy. A child encountering this object for the first time might notice different relations between its properties: a ball bearing is the mechanism that enables spinning (a mechanistic relation); spinning serves the function of relieving nervous energy (a functional relation); finally, all these properties are tied to being a member of the category “fidget spinners” (a categorical relation). Each relation can potentially support generalizations to new objects. For instance, other objects might spin in a similar way because they have ball bearings (the mechanistic relation), because they are for relieving nervous energy (the functional relation), or because they are fidget spinners (the categorical relation). How do children navigate this space of possibilities?

In the current paper, we test the hypothesis that explanations help children generalize from known to novel cases by highlighting some relations as more inductively powerful than others. Specifically, the child who learns that the object spins “because it has a ball bearing” might be more inclined to generalize the property of spinning on the basis of the mechanistic relation than the child who learns that it spins “because it is a fidget spinner,” even if both children know that all three relations (mechanistic, functional, and categorical) obtain (see also Lombrozo & Wilkenfeld, 2019).

This example suggests that when we explain, we do more than identify true claims about a particular case: we highlight generalizable patterns that extend beyond the observation being explained (Heider, 1958; Quine & Ullian, 1970). Indeed, according to the

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“Explanation for Export” proposal (Lombrozo & Carey, 2006), one function of explanation is to support generalization beyond the specific case being explained.

Consistent with these proposals, empirical work with adults suggests that explanations play an important role in guiding generalization. For example, Sloman (1994) found that adults were more likely to generalize a property from a known to a novel case when the explanation for the known case plausibly held for the novel case. Likewise, Vasilyeva and Coley (2013) showed that an individual’s explanation for a property predicted the generalizations they would subsequently suggest (e.g., if substance B6 is found in ducks, what else is likely to have substance B6?). They additionally found that different *types* of explanations corresponded to different *types* of generalizations. When participants generated category-based or functional explanations (e.g., ducks have it because “it’s a bird thing” / because “it protects them from the cold”), they tended to project the property to targets related categorically rather than ecologically (e.g., to “other birds” rather than “their predators”). However, this tendency was reversed for mechanistic explanations (e.g., “they got it from their food”), which were associated with inferences based on ecological relations. Similarly, in an experimental task, Lombrozo and Gwynne (2014) found that participants who received either a mechanistic or functional explanation favored generalizations that preserved the relationship featured in the explanation.

Further reinforcing the connection between explanation and generalization in adult cognition, Vasilyeva, Wilkenfeld, and Lombrozo (2017) documented the reverse direction of influence: people’s expectations about future generalizations affected how much they liked different explanations. Participants were led to expect that they would later make inferences about the presence or absence of a property based on information about causal mechanisms, functions, or category membership. When asked to rate mechanistic, functional, and categorical explanations, participants favored explanations that were based on the kind of information they expected to be useful for their subsequent generalization decisions.

Although there is good evidence that adults can use explanation to guide generalization, it is unclear how this ability develops across the lifespan. Do young children coordinate explanations and generalizations from the moment they appreciate the distinctions between different kinds of explanations? Or does this ability emerge in a more gradual or piecemeal fashion, such that children only demonstrate such coordination at an older age? In the current paper, we investigate whether 4–5 and 6–7-year-old children are more likely to generalize a property on the basis of a shared feature (a causal mechanism, function, or category membership) after hearing an explanation citing a mechanistic, functional, or categorical relationship. This pattern would suggest a capacity to use explanations to inform subsequent generalizations.

Examining how the coordination between explanation and generalization develops is important because it offers insights into one of the most basic questions in cognitive development: how children learn so much from limited input. Specifically, how do children constrain the range of hypotheses they entertain when generalizing from the known to the unknown? The explanations received from adults or peers could provide one crucial source of constraint, directing children to the generalizations that are most likely to be useful. Indeed, a large literature suggests that seeking, generating, and receiving explanations is a powerful basis for learning (Chi, de Leeuw, Chiu, & LaVancher, 1994; Lombrozo, 2012, 2016; Wellman, 2011). The link between explanations and inductive potential could be one reason explanation has such powerful effects. While explanation and generalization have both been the targets of much developmental research, a direct test of how one informs the other in children is notably absent.

Some indirect evidence of early explanatory sophistication suggests that the coordination between explanation and generalization could be in place by age four or five. Children as young as two years of age provide and seek explanations (Callanan & Oakes, 1992; Hickling & Wellman, 2001), and they begin to differentiate explanations from non-explanations by age three (Frazier, Gelman & Wellman, 2016). There is also evidence that explanation is coordinated with other representations and judgments from an early age (e.g., three- to four-year-olds invoke domain-appropriate mechanisms in their explanations, Hickling & Wellman, 2001; Inagaki & Hatano, 2006; see also Sobel, 2004).

Prior work also suggests that young children differentiate between different *types* of explanations (mechanistic, functional, and categorical). By age four, children request explanations of different types in different domains (Greif, Kemler Nelson, Keil, & Gutierrez, 2006), successfully generalize the form of an explanation (i.e., mechanistic versus functional) to novel cases (Lombrozo, Bonawitz, & Scalise, 2018), and appreciate when formal (categorical) explanations are appropriate (Howard, Wagner, Carey, & Prasada, 2018). There is also evidence that through grade school, children favor functional over mechanistic explanations (Kelemen, 1999; but see Keil, 1996; Lombrozo et al., 2018).

Finally, there is a great deal of evidence demonstrating that receiving and generating explanations can affect learning and inference (e.g., Wellman & Lagattuta, 2004; Walker, Lombrozo, Legare, & Gopnik, 2014; Walker, Lombrozo, Williams, Rafferty, & Gopnik, 2017; Ruggeri, Xu & Lombrozo, 2019). For example, Walker et al. (2014) found that prompting three- to five-year-old children to explain why objects made a machine go led them to privilege causal properties, as opposed to appearance, as a basis for generalizing internal properties and category membership.

Despite this evidence of explanatory sophistication in the preschool years, a handful of findings suggest that explanation is somewhat quarantined from prediction, at least until age four. Specifically, several studies have found an “explanation advantage,” such that successful explanation precedes accurate prediction. For instance, children are able to explain why someone avoided a contaminated food before they can predict the same event (Amsterlaw & Wellman, 2006; Legare, Wellman, & Gelman, 2009). Wellman (2011) explains this progression in terms of the difference between *postdiction* and *prediction*: in the former case an additional piece of information (the outcome) is known. As a form of postdiction, explanation could involve a lower cognitive burden and serve as a stepping stone to prediction.

By age eight, children are capable of generating sophisticated and context-appropriate explanations and predictions, but they do not yet show adult-like coordination between explanations and generalization. For example, one child in Vasil and Coley (in prep.) explained why a zebra and savannah grass are both sick with the same disease by appeal to causal transmission from grass to zebra:

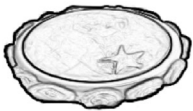
Table 1

Sample script from an incongruent trial (mechanistic explanation, function-based generalization). Arrows were not presented. A sample congruent trial is illustrated in the [Online Supplement, Table S2](#).

Learning phase:



Explanation phase:



Here's one. Why is it sticky? Let's ask my friend Mike. Mike sometimes says things that are smart, and sometimes says things that are silly. Let's see what Mike thinks!

Mike, why is this sticky?



Because it has special tape on one side!

Mike says it is sticky because it has special tape on one side.

[Explanation rating]
What do you think about Mike's explanation?

Is it a good explanation or is it a bad explanation?



Is it really [good/bad] or is it kinda [good/bad]?



Ok, remember, Mike said it is sticky because it has special tape on one side.

Generalization phase:



Now, There is something in this box. Julia wants to know if it is sticky. I don't know. But let's see what the box says.
[Experimenter flips the box label]. It says that *it can pick up marbles*.

[Generalization rating] Do you think it is sticky or not sticky? Is it for sure (not) sticky or maybe (not) sticky?

“because it eats grass.” Yet when asked what else might be sick with the same disease, the child relied on a completely independent basis for generalization, saying “a werewolf, because both zebras and werewolves have a tail.”

Summing up this research, there are good reasons to expect that even young children can effectively learn from explanations, suggesting some rudimentary level of coordination between explanation and subsequent generalizations. At the same time, the coordination of explanation and prediction is tenuous at age four (as reflected in the “explanation advantage” and other evidence of explanation-prediction asymmetries, Nancekivell & Friedman, 2017), and still fragile at age eight (Vasil & Coley, *in prep.*). In the present study, we thus focused on four- to seven-year-olds as an age range within which we might expect to see developmental change in the coordination of explanation and generalization.

The goal of this study was to investigate when and how children begin to use explanations as a guide to subsequent generalizations. Children received and evaluated a mechanistic, functional, or categorical explanation for the property of a novel object, and then guessed whether that property generalizes to a hidden object, knowing only that it shares a mechanism, function, or category membership with the initial object. The main manipulation concerned the “congruence” between the presented explanation and the feature shared by the two objects. On *congruent* trials, the two objects shared the feature invoked in the explanation. For example, after hearing a mechanistic explanation (“It is sticky because it has a special tape on one side”), a participant was presented with a hidden object sharing the same mechanism invoked in the explanation (“it has a special tape on one side...do you think it is sticky?”). On *incongruent* trials, the explanation mentioned one feature (e.g., mechanistic), but the hidden object shared a different feature (e.g., functional, “it can pick up marbles”). This procedure involved an adaptation of classic category-based induction tasks, which have been used to study children’s and adults’ generalization for decades (Coley, 2012; Gelman & Coley, 1990; Gelman & Markman, 1986; Heit, 2000; Heit & Rubinstein, 1994; Kalish & Gelman, 1992; Osherson, Smith, Wiklie, López, & Shafir, 1990; Rips, 1975; Ross & Murphy, 1999; Sloman, 1994; see Hayes & Heit, 2013, for review).

The first key question was whether generalization and explanation are coordinated by age four, and whether this coordination undergoes any change between ages four and seven. If children rely on explanations to guide their generalizations, they should generalize more confidently on explanation-congruent than on explanation-incongruent trials. If, in contrast, they generalize from known to unknown objects simply based on the fact that they share properties (tracking the truth status of shared relationships rather than their explanatory relevance), their generalizations should be insensitive to the preceding explanation (i.e. not vary across congruent vs. incongruent trials). The capacity to recognize variability in explanatory relevance across true statements increases between ages four and five (Johnston, Sheskin, & Keil, 2019), suggesting that we might see a shift towards increased reliance on explanation in generalization in our targeted age range.

The second question was whether effective coordination depends on the *type* of explanatory relationship involved (i.e., mechanistic, functional, or categorical). Coordination might emerge earlier for the kinds of relationships that are most widely applicable (arguably mechanistic), for those that figure in favored kinds of explanations (arguably functional; Kelemen, 1999), or for those that dominate children’s early generalizations (arguably categorical; Coley, 2012).

2. Method

2.1. Participants

We recruited 54 4- and 5-year-olds (range 48–71 months, $M = 61$ months, $SD = 7$ months) and 54 6- and 7-year-olds (range 72–95 months, $M = 82$ months, $SD = 8$ months) in museums and preschools in the Bay Area, California. An additional eight children were excluded due to equipment failure (six children) or experimental error (two children). The study was approved by the University of California Berkeley Committee for Protection of Human Subjects.

2.2. Materials, design and procedure

The test session consisted of three trials, each comprising three phases: learning, explanation, and generalization (see Table 1 for a sample trial, and Online Supplement Tables S1 and S2 and Fig. S1 for additional materials).

In the *learning phase*, the experimenter introduced a novel type of object (e.g., a “dax”) and presented three features forming a causal chain, in a fixed order (e.g., they have special tape on one side → are sticky → can pick up marbles). Objects and features were illustrated on colorful cards, laid out one by one as features were introduced. The causal chain was repeated once.

In the *explanation phase*, the experimenter laid out a black-and-white silhouette of the same object type (e.g., a dax), and asked a why-question about the middle feature in the causal chain (e.g., “Why is it sticky?”), addressing a puppet on a laptop screen (who had been described as someone who says both smart and silly things). In a short video, the puppet provided an explanation. The explanations were either mechanistic (citing the preceding feature in the causal chain: “because it has special tape on one side”), functional (citing the final feature in the chain: “because that way it’s easy to pick up marbles”), or categorical (citing category membership: “because it’s a dax”). The child was then asked to evaluate the explanation using a two-step, four-point thumb scale ranging from “really bad” to “really good”: the child was first asked whether the explanation was good or bad, which was followed up with “is it really [good/bad], or is it kinda [good/bad]?” We adopted this two-step rating method in order to make it easier for young children to generate 4-point ratings, without overwhelming them with four choices at the outset. After the explanation evaluation, the experimenter repeated the explanation and removed all the pictures.

In the *generalization phase*, the experimenter presented a closed box with a transparent pocket holding a face-down card representing an object feature. The experimenter said that another puppet wanted to know if the object in the box had a certain feature

(always the middle feature from the causal chain, e.g., being “sticky”); the experimenter said she did not know the answer, but they could check what the box said. The experimenter flipped the card, revealing a picture representing one of the features (mechanism, function, or category membership), and asked the child to make a guess about the hidden object (“Do you think it is sticky or not sticky?”). This was followed by “For sure [sticky/not sticky], or maybe [sticky/not sticky]?”, producing a 4-point rating. Then the box was removed, and the next trial began.

The solicited generalizations were based on a shared mechanism, function, or category membership. Generalizations were either explanation-congruent (on one trial) or explanation-incongruent (on two trials; an equal number of congruent and incongruent trials could not be generated with three explanation types and three generalization types without recycling any across trials). On congruent trials, the generalization target and the original object shared the feature invoked in the preceding explanation. For instance, if a functional explanation was offered in the explanation phase, a congruent generalization trial would involve generalizing based on the shared function, and an incongruent generalization trial would involve generalizing based on the shared mechanism or category membership.

The pairing between the three objects, three explanation types, and three generalization types was counterbalanced using a Latin square design, producing nine unique conditions. Across the three trials, each participant evaluated one explanation of each type, introduced by different puppets. Across participants, each explanation type was paired with each object and each generalization type.

3. Results

Due to experimental error or equipment failure, data from one explanation trial and four generalization trials were lost (two younger and two older children). For a given analysis, trials with missing data were excluded. Explanation and generalization ratings were treated as ordinal variables with four levels, and analyzed in ordinal logistic regressions using the “ordinal” package in R. Explanation type, generalization type and congruence were treated as categorical predictors; age (in months) was treated as a continuous predictor except when specified otherwise. The significance of higher-level effects was determined by model likelihood ratio tests. To assess lower-level effects (e.g. the effect of explanation type within each age group), we queried the full regression model varying the reference group for the categorical predictors. For pairwise comparisons we report the odds ratios (OR), i.e. exponentiated odds ratio coefficients from ordinal logistic regressions. These can be interpreted as the relative difference between the odds of transitioning to the next level of the ordinal outcome variable, comparing levels of the predictor variable.

3.1. Explanation evaluation

An ordinal logistic regression predicting explanation ratings from explanation type (mechanistic, functional, categorical) and centered age in months, allowing for random intercepts across participants, revealed that both explanation type (likelihood ratio $LR = 39.96$, $df = 2$, $p < .001$) and age ($LR = 21.91$, $df = 1$, $p < .001$) significantly predicted explanation ratings. Mechanistic explanations were rated higher than functional explanations, $OR = 1.87$, $z = 2.09$, $p = .037$, and higher than categorical explanations, $OR = 6.01$, $z = 5.72$, $p < .001$; functional explanations also received higher ratings than categorical explanations, $OR = 3.22$,

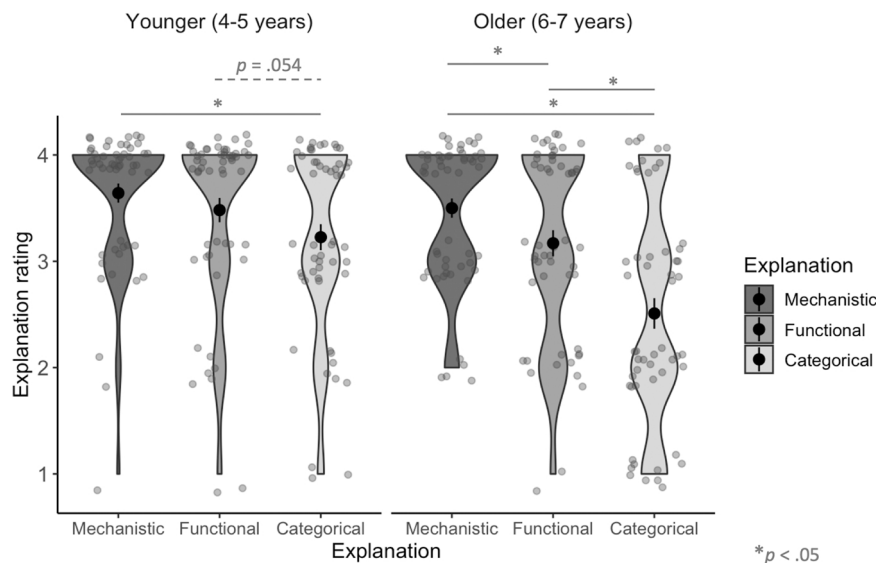


Fig. 1. Distribution of explanation evaluation ratings as a function of explanation type and age group. Violin width is proportional to the number of participants giving the corresponding explanation rating. Gray dots show jittered raw data. Group means and standard errors (shown as black dots with error bars, $\pm 1SE$) are displayed for reference only; the analyses treated evaluation ratings as an ordinal variable. Additional summary statistics are available in the online supplement, [Table S3](#).

$z = 4.08, p < .001$. Overall, ratings decreased with age, $OR = 0.95, z = -4.54, p < .001$. These effects were qualified by a marginally significant interaction, $LR = 5.65, df = 2, p = .059$. We explored the interaction further by switching to the categorical age predictor and examining the effect of explanation type in the younger (4–5-years-old) and older (6–7-years-old) age groups. As shown in Fig. 1, older children differentiated all three explanation types, rating mechanistic explanations higher than functional ($OR = 2.27, z = 2.06, p = .040$) and categorical ($OR = 10.73, z = 5.66, p < .001$), and rating functional explanations higher than categorical ($OR = 4.73, z = 3.99, p < .001$). Younger children showed a less pronounced pattern of differentiation: they rated mechanistic explanations higher than categorical ($OR = 3.25, z = 2.77, p = .006$), but their ratings of functional explanations were only marginally higher than those of categorical explanations ($OR = 2.23, z = 1.93, p = .054$), and their ratings of mechanistic and functional explanations did not differ ($z = 0.85, p = .395$).

3.2. Property generalization

Collapsing across offered explanation types, an ordinal logistic regression predicting generalization ratings from generalization type (cause-based, function-based, category-based) and centered age in months, allowing for random intercepts across participants, revealed no significant effects (all $ps \geq 0.123$). This suggests that the stimuli were well-matched across types, providing an even playing field on top of which the preceding explanations might exert some effect.

3.3. Relation between explanation and property generalization

We first examined whether generalization ratings were reliably higher for congruent trials (where participants made property generalization decisions based on the relationship cited in the preceding explanation of that property) vs. incongruent trials (where the relationship did not match across explanation and generalization). We fit an ordinal logistic regression predicting generalization ratings from congruence (explanation-congruent vs. explanation-incongruent generalization), centered age in months, and their interaction, allowing for random intercepts across participants. The key finding from this analysis was that children rated explanation-congruent generalizations significantly higher than explanation-incongruent generalizations, $LR = 4.89, df = 1, p = .027$. In a set of additional analyses, we explored whether the effect of congruence held within each generalization type, or if, on the contrary, it was restricted to a subset of generalizations. In other words, we assessed whether all three explanations were effective in guiding congruent generalizations. Each generalization type (cause-, function-, or category-based) was predicted from explanation congruence, in three separate ordinal regressions. Cause-based generalizations showed a significant boost from congruent (mechanistic) explanations, relative to incongruent explanations, $LR = 5.21, df = 1, p = .022$; function-based generalizations received a marginal boost from congruent (functional) explanations, $LR = 2.78, df = 1, p = .095$; category-based generalization was not affected by presence or absence of congruent (categorical) explanations, $LR = 0.04, df = 1, p = .851$. Mean generalization ratings as a function of generalization type and congruence are shown in Table 2.

Turning to the developmental effects, age in months did not predict generalization ratings, $LR = 2.40, df = 1, p = .121$, and the interaction between congruence and age was not significant, $LR = 0.86, df = 1, p = .355$. However, in accordance with our analysis plan, we report the planned contrasts examining the degree of coordination between explanation and generalization separately in the younger children and in the older children. We found that the older children rated congruent generalizations significantly higher than incongruent generalizations, $OR = 2.79, z = 2.58, p = .009$; in contrast, the younger children did not, $OR = 1.19, z = 0.45, p = .652$ (interaction between congruence and categorical age $LR = 2.32, df = 1, p = .128$). The response distributions shown in Fig. 2 suggest that the overall effect of congruence was driven primarily by a drop in explanation-incongruent generalization in older children. However, in the absence of a significant interaction, claims about developmental differences should be treated as highly tentative.

3.4. Effects of explanation quality

The preceding analyses indicate that whether an explanation is or is not congruent guides subsequent generalization (most likely by suppressing explanation-incongruent generalizations), and they suggest this effect might be driven by the older children in our sample. We next investigated whether this effect was moderated by children's perceptions of an explanation's quality, and whether we once again saw hints of a developmental trend, such that older children might show a more pronounced effect of explanation on subsequent generalization. Were this the case, we would expect older children to be more likely to generalize a property on the basis of some feature when they found an explanation that appealed to that specific feature good versus bad.

For this analysis, we recoded children's congruent explanation ratings as "high quality" if an explanation received a rating of 4, and as "low quality" otherwise. Thirty-six younger children (out of 54), and twenty-three older children (out of 54) rated congruent

Table 2

Generalization ratings as a function of generalization type, congruence, and age group. Means are followed in parentheses by standard deviations.

		Cause-based generalization	Function-based generalization	Category-based generalization
Younger children (4–5 years)	Congruent trials	3.67 (0.49)	3.67 (0.59)	3.56 (0.62)
	Incongruent trials	3.64 (0.59)	3.44 (0.82)	3.58 (0.69)
Older children (6–7 years)	Congruent trials	3.72 (0.46)	3.72 (0.57)	3.44 (0.70)
	Incongruent trials	3.15 (0.93)	3.22 (0.90)	3.53 (0.77)

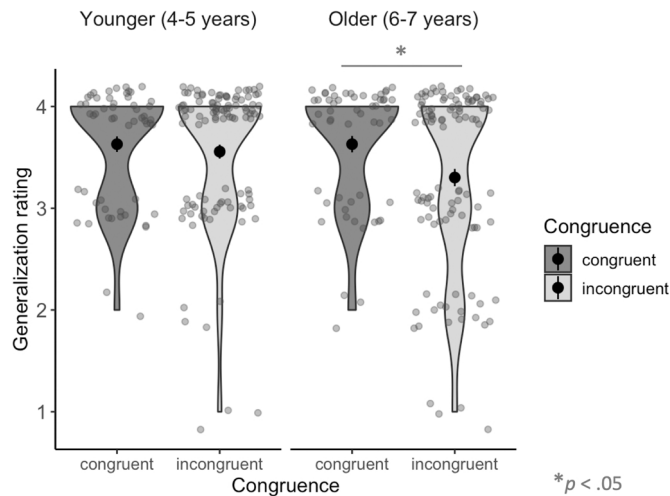


Fig. 2. Distribution of generalization ratings as a function of explanation-generalization congruence and age group. Each participant contributed three datapoints: one congruent generalization rating and two incongruent generalization ratings. Group means and standard errors (shown as black dots with error bars, ± 1 SE) are displayed for reference; the analyzes treated generalization ratings as an ordinal variable.

explanations as “high quality.” This re-coding of explanation ratings served the purpose of making the effective range of the predictor variable more comparable across the older and younger children, as the latter group rarely used low explanation rating scale points. (We originally intended to perform a median split, but the median for both age groups was 4, so we used the next closest split between ratings of 3 and 4. Splitting the scale at 2/3 produced the same pattern of results, but with a preponderance of “high quality” ratings, 46/54 younger and 40/54 older children.)

We then examined how these ratings predicted generalization, on congruent trials only, separately for the two age groups. Older children were significantly more likely to generalize on congruent trials if they had rated the preceding explanation as “high quality” vs. “low quality” ($LR = 4.31$, $df = 1$, $p = .038$). In contrast, the younger group showed no relationship between their ratings of explanation quality and subsequent generalizations ($LR = 0.42$, $df = 1$, $p = .516$).

4. Discussion

This study investigated the emergence of coordination between explanation and generalization in 4–7-year-old children. We found that children were significantly more likely to generalize a property on the basis of some feature if they had previously heard an explanation tying the property to that feature, with the strongest evidence for this association emerging for older children receiving mechanistic explanations. For example, hearing that an object is sticky “because it has special tape on one side” vs. “because it is a dax” influenced how children generalized the property to an unknown object. The effect of explanation is particularly striking because it cannot be attributed to differences in factual beliefs: all participants received the same information about the objects; everyone learned what the object properties were, how they were connected via mechanistic and functional relationships, and what the object labels were. It also cannot be discounted as an artifact of the experimenter drawing attention to a particular type of relation, or attributed to a low-level strategy of providing higher ratings when a generalization “matched” what came before. On these accounts, we would expect congruence effects to have been equivalent across explanation types, or even most pronounced for categorical explanations, which offered the simplest and most distinctive content to “match.” Instead, we found variability across explanation types, with categorical explanations offering the weakest evidence for effects of congruence.

Intriguingly, the effect of congruent explanation on subsequent generalization appeared to be driven by the older children in our sample, 6–7-years-olds. (Although the overall interaction did not reach significance, planned comparisons revealed significant differences; the trends are intriguing, but the evidence of developmental change should be interpreted with caution.) The effect of the explanation was greater for the children who judged it to be a *good* explanation, although again, this pattern only held for the older children.

We also found a pronounced developmental shift in how strongly children differentiated among kinds of explanations. While 6–7-year-olds reliably favored mechanistic explanations over functional explanations, and functional explanations over categorical explanations, the preferences of 4–5-year-olds were less differentiated. Despite developmental differences in the *strength* of explanatory preferences, the relative ordering of mechanistic, functional and categorical explanations remained stable. While many studies do find a preference for functional explanations for artifacts, preferences also depend on the quality of the specific explanations (for a discussion and data involving adults, [Liquin & Lombrozo, 2018](#) is relevant). In the current case, we speculate that the functional explanations may have been less compelling because they were unfamiliar. By contrast, prior work using artifacts has overwhelmingly used familiar objects with known functions.

Explanatory preferences were mirrored in the strength of the congruence effect across the three relationships: cause-based

generalizations were sensitive to the presence of congruent mechanistic explanations, but category-based generalizations were not; function-based generalizations showed an intermediate profile. Overall, these results reveal a coherent picture of increasing explanatory sophistication and emerging coordination between generalization and explanation, with explanations flagging relevant types of relationships between objects and their properties that support inferences to novel cases.

Our findings prompt a variety of follow-up questions about etiology and on-line mechanisms. Speculating about possible developmental trends, what might change between ages 4–5 and 6–7, such that greater coordination between explanation and generalization might emerge alongside greater differentiation between different types of explanations? One possibility is that such developmental changes could be driven by children's growing knowledge of the relevant relationships, and/or by increasing capacity to differentiate among explanatorily relevant vs. irrelevant true information (Johnston, Sheskin, & Keil, 2019) or historical vs. ahistorical functions (Lombrozo & Carey, 2006; Lombrozo & Rehder, 2012). However, it could also be that capacities for explanatory discrimination and flexible generalization bootstrap each other. It also remains an open question whether congruent explanations promote generalization, or incongruent explanations suppress generalization.

Another open question concerns the role of pedagogy in our task. Rather than presenting children with an explanation from an authoritative source, children in our study were presented with an explanation from a puppet who “sometimes says things that are silly,” and they were then asked to evaluate the explanation themselves. It is plausible that presenting an expert explanation in a pedagogical context would have generated stronger effects on subsequent generalizations. It is also possible that such explanations would not only encourage some generalizations, but actively restrict others, much like pedagogical demonstrations can discourage children from more open-ended exploration (Bonawitz, Shafto, Gweon, Spelke, & Goodman, 2011). This could be the “dark side” of explanations' positive inductive role: by encouraging learners to favor some inductive hypotheses over others, an explanation could restrict some forms of exploration or inference (see also Legare, 2012).

Finally, our findings invite further investigation concerning the generalizability of the observed patterns beyond the domain of artifacts, as well as across cultural and educational contexts. Prior work has found variability in the strength of children's preferences for teleological explanations across domains (e.g., Kelemen, 1999), raising the possibility that the coordination of explanation with generalization may vary across domains, as well. A broader question is whether, for a given observation in a given domain, people prefer to generalize based on the explanations they find most believable or appealing (be they categorical, mechanistic, or functional), or whether some types of explanation – mechanistic and/or functional – are generally privileged as more solid bases for generalization than categorical explanations, across domains. A cross-cutting set of questions concerns the origins of explanatory preferences, whether domain-general or specific: to what extent are they shaped by educational and cultural experiences, whereby teachers and other knowledgeable members of a community signal to the child what explanation types should be favored? These are important questions that a comprehensive account of how explanation and induction interact across development will need to address.

In sum, our findings document an important source of guidance in children's inductive generalizations: explanations of prior observations. Consistent trends in our data point to an important developmental transition: from generalization unconstrained by explanation, to generalization *guided* by it. As children master the coordination of explanation and generalization, they can increasingly benefit from the advantages enjoyed by adults, including the ability to effectively constrain a range of inductive hypotheses to the most relevant and plausible subset, and to generate flexible inferences from the same observation depending on one's context and goals (Vasilyeva & Coley, 2013; Vasilyeva et al., 2017). The increasing capacity to discriminate among good and bad explanations (whether offered by others or internally generated) is an important scaffolding for children's ability to make principled inductive guesses and navigate the world of uncertainty.

At the same time, by focusing on inductively rich relationships that good explanations extract from the world, learners may miss out on some forms of broader exploration or inference that have been shown to facilitate the discovery of unconventional but true models of the world (Bonawitz et al., 2011; Gopnik, Griffiths, & Lucas, 2015; Legare, 2012) – but such is the cost of becoming an adult.

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CRediT authorship contribution statement

Vasil, Ruggeri and Lombrozo designed the study. Lombrozo secured the funding. Vasil and Ruggeri collected the data and/or supervised data collection. Vasil analyzed the data and made the visualizations. Vasil prepared the original manuscript draft; Ruggeri and Lombrozo contributed extensive edits.

Declarations of interest

None.

Data availability statement

Anonymized data are available through OSF, https://osf.io/t43wy/?view_only=0cd60d01ebc1488d9c307424890711ad.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.cogdev.2021.101144](https://doi.org/10.1016/j.cogdev.2021.101144).

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