Journal of Experimental Child Psychology 126 (2014) 198–212

Contents lists available at ScienceDirect

Journal of Experimental Child Psychology

journal homepage: www.elsevier.com/locate/jecp

Selective effects of explanation on learning during early childhood

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ARTICLE INFO

Article history:
Received 11 August 2013
Revised 1 March 2014
Available online 16 June 2014

Keywords:
Causal explanation
Causal reasoning
Self-explanation
Learning
Generalization
Cognitive development
Early childhood

ABSTRACT

Two studies examined the specificity of effects of explanation on learning by prompting 3- to 6-year-old children to explain a mechanical toy and comparing what they learned about the toy's causal and non-causal properties with children who only observed the toy, both with and without accompanying verbalization. In Study 1, children were experimentally assigned to either explain or observe the mechanical toy. In Study 2, children were classified according to whether the content of their response to an undirected prompt involved explanation. Dependent measures included whether children understood the toy's functional–mechanical relationships, remembered perceptual features of the toy, effectively reconstructed the toy, and (for Study 2) generalized the function of the toy when constructing a new one. Results demonstrate that across age groups, explanation promotes causal learning and generalization but does not improve (and in younger children can even impair) memory for causally irrelevant perceptual details.

Introduction

A growing literature suggests that young children's explanations play a crucial role in learning (Bonawitz, van Schijndel, Friel, & Schulz, 2012; Legare, 2012, 2014; Legare & Gelman, 2014; Roy &

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http://dx.doi.org/10.1016/j.jecp.2014.03.001
0022-0965/

Chi, 2005; Siegler, 2002; Singer, Golinkoff, & Hirsh-Pasek, 2006; Sobel & Sommerville, 2009; Wellman & Liu, 2007). For example, generating explanations can improve acquisition of new material and its extension to novel cases (Crowley & Siegler, 1999; Lombrozo, 2006; Wellman, 2011) and can even accelerate difficult conceptual transitions such as acquiring an understanding of false beliefs (Amsterlaw & Wellman, 2006) or number conservation (Siegler, 1995). Despite the acknowledged importance of explanation during early childhood, however, little is known about how effects of explanation differ—if at all—from mere verbalization or general attention and whether and how effects of explanation are selective to particular kinds of learning. Here we explored whether prompting 3- to 6-year-old children to explain a mechanical device fosters causal–mechanical understanding more effectively than does observation or verbalization and, if so, whether such understanding comes at the expense of other kinds of learning.

Educational research comparing self-explanation—that is, explaining to oneself or another person—with other activities suggests that explaining can be more effective for learning than alternative activities such as thinking aloud and reading study materials twice, especially when it comes to generalizing from study material to new cases (see Fonseca & Chi, 2011, and Lombrozo, 2012, for reviews). Although most research on self-explanation has focused on older children and adults, the limited research with younger children suggests similar effects. For example, research on problem solving among elementary school children comparing the effectiveness of self-explanation with alternative activities (e.g., solving practice problems) found that self-explanation was associated with greater conceptual and procedural knowledge (McEldoon, Durkin, & Rittle-Johnson, 2012). Rittle-Johnson, Saylor, and Swygert (2008) also demonstrated that explanation prompts facilitate transfer in children as young as 5 years relative to repeating problem solutions in problem-solving tasks. Notably, however, children in these previous studies of self-explanation were asked to explain why a particular solution or strategy was correct; that is, they explained some task-relevant *feedback* (see also Amsterlaw & Wellman, 2006; Crowley & Siegler, 1999; Rittle-Johnson et al., 2008). It could be that effects of explanation in young children result from the interplay of feedback with their explanations. For example, explaining could draw attention to the feedback and encourage children to rephrase it in their own words, thereby facilitating belief revision. Thus, it is an open question whether simply explaining one's observations—in the absence of feedback of this type—can similarly improve young children's learning and, if so, whether its impact results from the general use of language or from explanation per se. This question is especially important in understanding the role of children's spontaneous explanations on learning throughout development (Legare, 2014).

Another open question concerns the selectivity of explanation's effects, especially during early childhood. In particular, are effects of explanation restricted to some kinds of learning, or do they extend more broadly? And do the benefits of explanation have any associated costs? Evidence from older children and adults suggests that effects of explanation can indeed be selective, improving some kinds of learning over others. For example, explanation can foster analogical transfer at the expense of memory for previous problems (Needham & Begg, 1991), privilege causal mechanisms over consistency with previous data in justifying causal judgments (Berthold, Roder, Knorzer, Kessler, & Renkl, 2011; Kuhn & Katz, 2009), and encourage learning about patterns instead of individual examples (Williams, Lombrozo, & Rehder, 2013). When it comes to effects of explanation during early childhood, however, comparable studies have not been performed and two distinct stories are quite plausible. On the one hand, explaining could boost general engagement or attention (e.g., Siegler, 2002), which might lead to relatively widespread benefits across wide-ranging measures of learning. On the other hand, consistent with research on older children and adults, explaining could privilege some kinds of learning (e.g., causal learning) at the expense of others (e.g., perceptual learning), leading to more selective effects and potentially even to impairments (see also Walker, Lombrozo, Gopnik, & Legare, 2014). Identifying whether and how effects of explanation are selective, therefore, is of both practical value (for informing educational practice) and of theoretical value (for helping to isolate the mechanisms by which explanation influences learning during early childhood).

Building on prior work, we propose that explanation generates selective effects and that it does so by encouraging young learners to consider particular kinds of hypotheses, namely those that support good explanations (Legare, 2012; Lombrozo, 2012; Williams & Lombrozo, 2013). If explanations are typically judged as better when they invoke causal mechanisms or broad generalizations (for reviews, see Keil, 2006; Lombrozo, 2006, 2012), then explaining could selectively focus learners' attention on hypotheses that exhibit these features. Consistent with these ideas, adults seek information about mechanisms when asked to explain an event (Ahn, Kalish, Medin, & Gelman, 1995; Keil, 2006; see also Bullock, Gelman, & Baillargeon, 1982; Koslowski, 1996; Lombrozo, 2010), and prompting adults to explain can foster the discovery and generalization of broad patterns (Williams & Lombrozo, 2010, 2013). In fact, a prompt to explain can lead even 3-year-olds to posit unobserved causes (Buchanan & Sobel, 2011; Legare, Gelman, & Wellman, 2010; Legare, Wellman, & Gelman, 2009) and favor generalizations that account for more observations (Walker, Williams, Lombrozo, & Gopnik, 2012), suggesting that prompts to explain might direct even young learners toward broad, causal patterns.

In the two experiments that follow, we provide the first empirical investigation of the selectivity of effects of explanation on young children's causal learning. Our studies differ importantly from prior work in that we did not provide children with direct instruction or corrective feedback. Moreover, we compared explanation with other tasks that were matched for time and verbalization, and we examined both causal and non-causal learning—learning about functional–mechanical properties versus memory for perceptual features such as color.

Our first objective was to differentiate effects of explanation from those due to observation (Study 1) or verbalization (Study 2). Our second objective was to examine whether and how prompts to explain selectively benefit young children's causal learning and whether this benefit comes at the expense of non-causal learning (Studies 1 and 2). Our final objective was to examine potential age-related differences in the effects of explanation on children's learning (Studies 1 and 2). In particular, we examined whether learning benefits are a consequence of children's age or instead follow from the content and quality of their explanations regardless of age.

In two studies, we presented preschool-aged children with a novel mechanical toy with visible interlocking gears and examined learning using measures that assessed their understanding of the toy's causal function, memory for the toy's non-causal properties such as color, and (in Study 2) generalization of the toy's causal function in constructing a novel toy. In Study 1, children were prompted to observe or explain the toy, and learning was assessed both as a function of the experimental manipulation and (for children in the explanation condition) based on the content of their verbal response (i.e., explanation vs. non-explanation). In Study 2, children provided verbal responses that were categorized as either explanations or non-explanations, and learning was assessed as a function of these categories. In the context of these studies, we defined explanations as responses that included functional or mechanistic information about the toy (i.e., about proximate causal processes or the function of a particular part or process) (see Kelemen, 1999; Legare et al., 2010; Lombrozo, 2009; Lombrozo & Carey, 2006).

Comparing effects of explanation with observation and non-explanatory verbalization can shed light on the mechanisms by which each process contributes to learning. If explanation's effects derive from greater attention or engagement, we might expect global improvements in learning relative to observation. If explanation's effects are a consequence of producing a verbal response, we might expect a benefit for explanation relative to observation in Study 1 and comparable effects for explanation and other verbalizations in Study 2. In contrast, we predicted that, relative to both observation and verbalization, explanation would improve learning on measures of functional–mechanical understanding (Studies 1 and 2) and generalization (Study 2) but would have no effect on—or even impair—learning about non-causal properties such as color.

Finally, our two studies also had the potential to differentiate several plausible trajectories for age-related changes in the effects of explanation on learning. One possibility was that explanation would help younger children more than older children because younger children may require greater scaffolding to achieve cognitive benefits that older children can achieve without prompting (for evidence that this is sometimes the case, see Walker et al., 2014). Another possibility was that explanation would help older children more than younger children because learning by explaining presumably requires some baseline level of verbal fluency and cognitive sophistication (Hickling & Wellman, 2001). A third possibility was that older children would be more likely than younger children to engage in (high-quality) explanation (Legare et al., 2010) but that effects of explanation among those who do explain would be relatively uniform across ages. Finally, effects of explanation could vary across development in their selectivity; for example, it could be that explanation privileges causal learning at the expense of perceptual memory in younger children but promotes causal learning without this penalty in older children. By investigating effects of explanation on learning across the 3- to 6-year age range—which spans a wide range of verbal, conceptual, and cognitive development—our studies could also help to differentiate these alternative developmental trajectories.

Study 1

Study 1 examined the selectivity of explanation's effects on children's learning about a causal system. We presented young children with a novel mechanical toy and compared learning across conditions in which they were or were not prompted to explain (*explanation* vs. *observation*). We measured two kinds of learning: learning about causal–mechanical relationships and learning about causally irrelevant properties such as color. We hypothesized that explanation would direct learners' attention toward causal mechanisms, resulting in better learning on measures of causal knowledge but not necessarily on measures of memory for causally irrelevant properties.

Method

Participants

A sample of 95 children—31 3-year-olds (M = 41.83 months, SD = 3.40), 32 4-year-olds (M = 53.56 months, SD = 3.14), and 32 5-year-olds (M = 65.34 months, SD = 3.34)—participated in Study 1. Children were recruited from preschools in a major metropolitan area in the American Southwest. The sample was approximately gender balanced and primarily Euro-American and middle class, with an approximately equal number of children from each age group assigned to each condition. Children were tested in a quiet room in the preschool or a research laboratory at a major southwestern university; each session took approximately 10 to 15 min. An additional 5 children participated but were dropped from the final sample due to either inability to engage with the task (n = 2) or experimenter error (n = 3). None of the participants from Study 1 participated in Study 2.

Materials

Materials included a novel machine with five interlocking gears, including a crank that made a fan turn and non-functional peripheral parts connected to selected gears (see Fig. 1A). Each child saw the

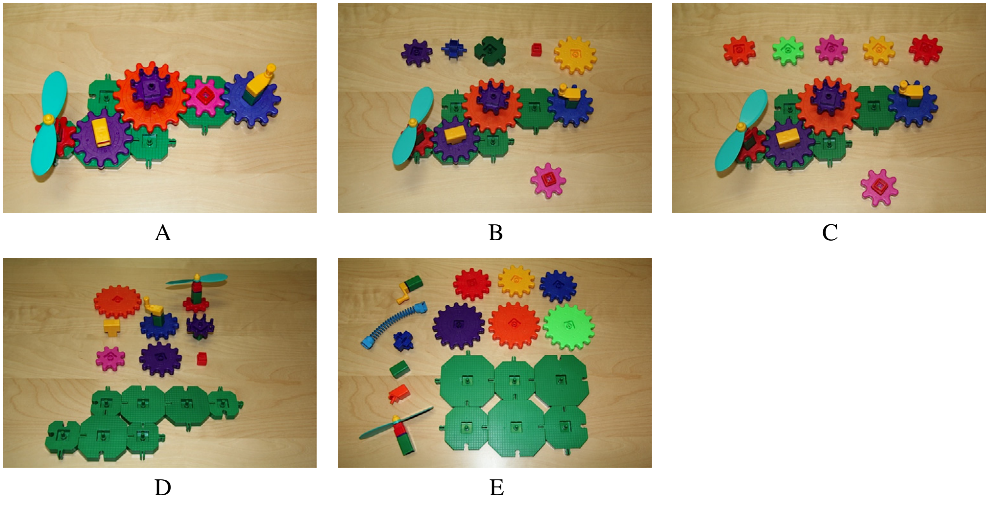

Fig. 1. (A) Studies 1 and 2: Machine used for experimental task. (B) Studies 1 and 2: Causal choice task stimuli. (C) Studies 1 and 2: Color choice task stimuli. (D) Studies 1 and 2: Reconstruction task stimuli. (E) Study 2: Generalization task stimuli.

same machine. An additional three parts were used in a training trial, and an additional 10 parts were used to assess learning (see "Procedure" section below).

Procedure

Training task. Each child participated in a training task where an experimenter demonstrated how the machine parts fit together. The child was presented with a base part, a gear, and a peripheral part (called a "topper"). The parts were similar, but not identical, to those used for the machine in the experimental task. The experimenter showed the child each part, labeling it as a base piece, gear, or topper, and then modeled how to put them together. Then the parts were taken apart, and the child was given the opportunity to put them together.

Experimental task. Following the training task, the experimenter placed the previously hidden machine in front of the child, pointed out the crank and fan, and turned the crank to demonstrate that this made the fan turn. In the *observation* condition, the child was told, "Let's look at this!", and then had 40 s to observe the machine (which was no longer in motion). In the *explanation* condition, the child was asked, "Can you tell me how this works?", and then had 40 s to produce a verbal response.[1]

Learning measures. After 40 s, the machine was removed from the child's view and placed under the table. Unbeknownst to the child, the small pink gear was removed from the machine and the machine was placed on the table again. The experimenter indicated that this was the same machine as before but that one of the parts was missing. The child then participated in two learning tasks, with order counterbalanced across participants.

For the *causal choice* task, five parts were presented, none of which was identical to the missing part. The choices consisted of one part of the correct size and shape but different color, one part of the correct shape but incorrect size, one part of the correct size but incorrect shape, and also a distracter part and a peripheral part seen before but not the correct shape (see Fig. 1B). The child was asked, "Can you point to which one of these parts you think will make it work?" This task was intended to assess children's understanding of the causal contributions of the gears in making the machine work—an aspect of functional–mechanical understanding.

For the *color choice* task, the experimenter presented the child with another five parts. All parts were the correct size and shape, but only one part was the same color as the original (see Fig. 1C). The child was asked, "Can you point to the piece that will make my machine look like it did in the beginning?" This task was intended to assess children's memory for the color of the original gear, a property irrelevant to functional–mechanical understanding.

After the choice tasks, the machine was again removed from the child's view under the table. The experimenter removed all of the parts from the base and took the peripheral parts off the medium-sized purple gear, the large orange gear, and the small pink gear. The crank gear and the fan gear were not taken apart. The experimenter put the base on the table in front of the child as before. Then the experimenter put the gears and peripheral parts in front of the child in a predetermined random order (Fig. 1D) and asked, "Can you put my machine back together the way it was before and make it work?" The child was given 10 min to reconstruct the machine.

Coding

Experimental task. For children in the explanation condition, verbal responses were coded for the presence of explanations. If the child provided a mechanistic or functional explanation (i.e., made a claim about proximate causal processes or the goal or function of a particular part or process; see Kelemen, 1999; Lombrozo, 2009; Lombrozo & Carey, 2006), the verbal response was coded as an *explanation* (e.g., "That [the crank] spins around and the others spin around," "It spins together"). All other verbal

[1] For both Studies 1 and 2, the complete experiments included conditions in which children were allowed to explore the toy. In the current article, we report data from the conditions that did not involve exploration, in line with our focus on effects of explanation versus matched controls (observation or verbalization). We found that children frequently engaged in spontaneous explanation during exploration, making it impossible to isolate the effects of explanation from exploration in those conditions. The results of the exploration conditions neither support not conflict with any claims in the current article.

responses were coded as *non-explanations*. Non-explanations included descriptions, inquiries, statements of uncertainty, and no responses. Verbal responses were coded by two independent coders with agreement of 94% (kappa = .83). Disagreements were resolved by discussion.

Learning tasks. For the causal choice and color choice tasks, selecting the correct part was scored as 1 and selecting an incorrect part was scored as 0. For the *reconstruction* task, success was analyzed along two dimensions: successfully reconstructing the machine's function (*causal reconstruction* score) and successfully reconstructing causally irrelevant components (*topper reconstruction* score). The child received a causal reconstruction score of 1 for successfully reconstructing the causal–functional relationships that would allow the machine to work (i.e., replacing the fan and handle correctly, replacing the gears correctly, interconnecting the gears, and spinning the handle during reconstruction) or otherwise received a score of 0. The topper reconstruction score reflected accuracy in pairing each gear with its non-functional peripheral part (1 = all correct, 0 = any incorrect).

Because the causal choice task and the causal reconstruction score both reflect causal learning, these scores were combined into a single *causal learning* score that could range from 0 (success on neither task) to 2 (success on both tasks). Similarly, because the color choice task and the topper construction score both reflect learning about non-causal aspects of the machine, they were combined into a single *non-causal learning* score that could range from 0 to 2.

Results

Learning as a function of experimental condition

Table 1 reports the proportions of correct responses as a function of condition (observation vs. explanation) for the four learning measures (causal choice, color choice, causal reconstruction, and topper reconstruction). To analyze performance, we conducted a repeated-measures analysis of variance (ANOVA) with type of learning score (causal learning or non-causal learning) as a within-participants factor and condition (observation or explanation) and age group (3-, 4-, or 5-year-olds) as between-participants factors. This analysis revealed a significant interaction between type of learning and condition, $F(1, 89) = 38.30$, $\eta_p^2 = .30$, $p < .001$, as well as an interaction among learning score, condition, and age group, $F(2, 89) = 7.48$, $\eta_p^2 = .14$, $p < .001$. Therefore, we analyzed performance for each learning score separately.

Analyzing causal learning scores revealed that participants in the explanation condition ($M = 1.04$, $SD = .65$) performed significantly better than those in the observation condition ($M = .49$, $SD = .66$), $F(1, 89) = 18.74$, $\eta_p^2 = .17$, $p < .001$, consistent with our predictions (Fig. 2). In addition, there was a main effect of age, $F(2, 89) = 4.99$, $\eta_p^2 = .10$, $p = .009$; post hoc tests revealed that 3-year-olds ($M = .48$, $SD = .57$) performed significantly worse than 4-year olds ($M = .88$, $SD = .71$), $t(61) = -2.41$, $p = .019$, and 5-year-olds ($M = .94$, $SD = .76$), $t(61) = -2.68$, $p = .010$, who did not differ from each other, $p = .734$.

Analyzing non-causal learning scores revealed that participants in the explanation condition ($M = .46$, $SD = .62$) performed significantly *worse* than those in the observation condition ($M = .89$,

Table 1
Study 1: Proportion of correct responses on each dependent measure by condition and age group.

Condition	Age group	Causal choice task score	Color choice task score	Causal reconstruction score	Topper reconstruction score
Observation	3 years	.13 (.09)	.27 (.12)	.07 (.07)	.60 (.13)
	4 years	.19 (.10)	.50 (.13)	.31 (.12)	.81 (.10)
	5 years	.37 (.13)	.25 (.11)	.38 (.13)	.25 (.11)
	Total	.23 (.06)	.34 (.07)	.26 (.06)	.55 (.07)
Explanation	3 years	.44 (.13)	.19 (.10)	.31 (.12)	.13 (.09)
	4 years	.50 (.13)	.25 (.11)	.75 (.11)	.13 (.09)
	5 years	.56 (.13)	.31 (.12)	.56 (.13)	.38 (.13)
	Total	.50 (.07)	.25 (.06)	.54 (.07)	.21 (.06)

Note. Standard errors of proportions are in parentheses.

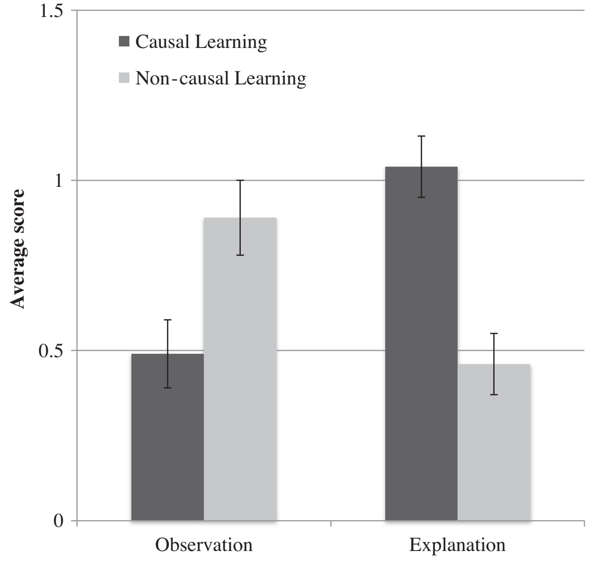

Fig. 2. Study 1: Causal and non-causal learning scores by condition.

$SD = .73$), $F(1, 89) = 11.15$, $\eta_p^2 = .11$, $p = .001$ (Fig. 2). In addition, there was a significant interaction between condition and age, $F(2, 89) = 6.50$, $\eta_p^2 = .13$, $p = .002$. A prompt to explain led to significant impairments on the non-causal learning measures for 3-year-olds, $t(29) = 2.29$, $p = .030$, and 4-year-olds, $t(30) = 4.34$, $p < .001$, but not for 5-year-olds, $t(30) = -0.86$, $p = .397$.

Verbal responses for the explanation condition

The coding of verbal responses from children in the explanation condition resulted in 38 children designated as *explainers* (10 3-year-olds, 14 4-year-olds, and 14 5-year-olds) and 10 children designated as *non-explainers* (6 3-year-olds, 2 4-year-olds, and 2 5-year-olds). Although there was a trend for older children to produce more responses coded as explanations than younger children, the distribution of designations did not differ significantly across age groups, $p = .17$.

We analyzed the relationship between children's verbal response designation (explainer or non-explainer) and their performance on the causal and non-causal learning tasks with a repeated-measures ANOVA[2] using type of verbal response as a between-participants factor (explainer or non-explainer), age group as a between-participants factor (3-, 4-, or 5-year-olds), type of learning as a within-participants factor (causal learning or non-causal learning), and learning score as the dependent measure. This analysis revealed the predicted interaction between designation and type of learning, $F(1, 46) = 19.90$, $\eta_p^2 = .32$, $p < .001$. On measures of causal learning, children who explained ($M = 1.21$, $SD = .58$) outperformed those who did not ($M = .40$, $SD = .52$), $t(46) = -4.03$, $p < .001$. But on measures of non-causal learning, children who explained ($M = .42$, $SD = .55$) performed no better than those who did not ($M = .60$, $SD = .84$), $t(46) = 0.81$, $p = .42$. There was no reliable main effect of age, $F(2, 44) = 1.59$, $p = .21$, and a marginal main effect of designation, $F(1, 44) = 3.18$, $p = .08$.

Discussion

The primary objective in Study 1 was to investigate the selectivity of explanation's effects on young children's learning. The data suggest that the benefits of explanation are indeed selective; although

[2] The non-parametric version of a repeated-measures ANOVA (Friedman's test) produced identical results for all measures in both studies.

children prompted to explain performed better on measures of causal learning, they performed significantly worse when it came to non-causal learning. This suggests that effects of explanations did not result from an indiscriminate increase in attention or engagement but rather were a consequence of the specific processes invoked through explanation. We also found age-related improvement in performance; the 4- and 5-year-olds outperformed the 3-year-olds, and whereas 3- and 4-year-olds' explanation-prompted improvements in causal learning were accompanied by a penalty for non-causal learning, this was not observed among 5-year-olds.

Notably, although the majority of responses in the explanation condition included explanations, a substantial minority of responses did not. We found that the content of children's verbal responses was predictive of their performance on causal learning measures; children who provided an explanation had higher causal learning scores than children who did not provide an explanation. Thus, it is possible that the *content* of children's responses to an explanation prompt—and in particular whether they succeed in producing an explanation—predicts children's causal learning performance beyond mere verbalization or description. Study 2 sought to examine how explicit prompts to explain versus describe influence the extent to which children generate explanations and how their explanations relate to learning. Doing so also provided a natural control for effects of verbalization because all children were prompted to provide a verbal response.

Study 2

In Study 1, the explanation condition required a verbal response, whereas the observation condition did not. Moreover, participants in the explanation condition were instructed to explain with a potentially leading prompt—to tell the experimenter how the machine *works.* Thus, it is unclear whether children's explanations in the absence of a prompt about how the machine works would similarly direct learners to *causal* understanding. Study 2 addressed these concerns by requiring verbalization in response to a very undirected prompt in all conditions and by once more analyzing performance as a function of the content of children's responses.

In Study 2, children received a general prompt to either *explain* the machine or to *describe* the machine. By using these undirected prompts, we hoped to experimentally alter the proportion of children providing explanations while also generating enough variability in the content of children's responses within each condition to permit a comparison of children who did and did not explain regardless of experimental prompt. Thus, the experiment involved two conditions—*describe prompt* and *explain prompt*—with all verbal responses also coded for the presence of explanations. We predicted that the content of children's verbal responses (i.e., generating an explanation) would predict performance on the learning measures; children who provided an explanation would perform better on causal learning measures than children who provided alternative responses and potentially mirror the impairments for non-causal learning observed in Study 1.

Study 2 also included an additional measure—generalization from one mechanical device to another. At the end of the task, participants were invited to create a new device. Given the close relationship between explanation and generalization (e.g., Lombrozo, 2012; Lombrozo & Carey, 2006), we anticipated that explanation would increase the extent to which children generalized the functional properties of the first machine to the second.

Method

Participants

A sample of 87 children (23 3-year-olds, 19 4-year-olds, 24 5-year-olds, and 21 6-year-olds) participated. Children were recruited from preschools in a major metropolitan area in the American Southwest. The sample was approximately gender balanced and primarily Euro-American and middle class, with an equal number of children from each age group assigned to each condition.

Although Study 1 revealed main effects of age on performance, the single interaction between age and effects of explanation suggested a break between the 3- and 4-year-olds, for whom explanation led to impairments on non-causal learning, and the 5-year-olds, for whom it did not. Given our otherwise small sample sizes, therefore, we grouped children into *younger* (3–4 years) and *older* (5–6 years) age groups for analysis in Study 2: 42 3- and 4-year-olds (M = 45.9 months, SD = 6.73) and 45 5- and 6-year-olds (M = 70.48 months, SD = 7.14).

Children were tested in a quiet room in their preschool or a research laboratory at a major southwestern university; each session took 10 to 15 min. An additional 5 children participated but were dropped from the final sample due to either inability to engage with the task (n = 2) or experimenter error (n = 3).

Materials

In addition to the materials from Study 1, there were 18 parts used during a *generalization* task (detailed below).

Procedure

Training task. The training procedure was identical to that in Study 1.

Experimental task. Following training, the experimenter placed the previously hidden machine in front of the child. In all conditions, the experimenter pointed out the crank and fan and turned the crank to demonstrate that this made the fan turn. Then the child observed the machine (which was no longer in motion) for 40 s in one of two conditions. In the *explain prompt* condition, the child was prompted with, "Explain the machine to me," which was followed up with "Can you explain anything else?" if the child stopped before the 40-s period ended. In the *describe prompt* condition, the child was told, "Describe the machine to me," with "Can you tell me anything else?" as a follow-up prompt. In both conditions, the child's responses were recorded on video.

Learning tasks. The learning tasks were identical to those in Study 1.

Generalization task. In the *generalization* task, the child was told, "Okay! Now I have new things to show you. Now it is your turn to make a machine." The child was provided with a new base made up of six interlocking base parts, six new gears, and six new peripheral parts. The base was preconstructed, and the peripheral parts and gears were laid out next to it in the same order for each child (see Fig. 1E). The child was given 3 min to create his or her own machine.

Coding

Experimental task. Children's verbal responses in the explain prompt and describe prompt conditions were coded for the presence of explanations as in Study 1. If children provided a mechanistic or functional explanation (i.e., made a claim about proximate causal processes or the goal or function of a particular part or process; see Kelemen, 1999; Lombrozo, 2009; Lombrozo & Carey, 2006), they were coded as *explainers* (e.g., "You just have to move it [the handle] around and then the fan turns around and the bottom things [points to middle gears] turn around too, and that top [peripheral part] spins too"). Children who did not make such statements were coded as *non-explainers.* Verbal protocols were coded by two independent coders with agreement of 91% (kappa = .86). Disagreements were resolved by discussion.

Learning measures and reconstruction task. The choice and reconstruction tasks were coded as in Study 1.

Generalization task. Children's behavior during the generalization task was coded for whether gears were placed on the base, whether gears interlocked, whether the handle and the fan were placed on gears on the base, and whether the gears with the handle and fan interlocked. Meeting all of these criteria successfully recreated the functional–mechanical basis of the original machine and corresponded to the *causal generalization* score, with success coded as 1 and failure coded as 0.

Results

Table 2 reports the proportions of correct responses as a function of children's verbal responses for the five key dependent variables (causal choice, color choice, causal reconstruction, topper reconstruction, and causal generalization) for younger and older children. Table 3 reports the proportions of correct responses as a function of children's verbal responses for the five key dependent variables (causal choice, color choice, causal reconstruction, topper reconstruction, and causal generalization) by age in years (3-, 4-, 5-, and 6-year-olds). Fig. 3 reports the average causal and non-causal learning scores, as detailed below.

Verbal responses

The verbal response coding resulted in 38 children designated as explainers (12 younger and 26 older) and 49 children designated as non-explainers (30 younger and 19 older). Children were equally likely to be designated as explainers versus non-explainers across the explain prompt and describe prompt conditions (17 of 41 vs. 21 of 46), $\chi^2(1, N = 87) = 0.1546$, $p = .694$; that is, the prompts were equally effective at generating explanations, potentially because children failed to differentiate between a request to explain and a request to describe. Moreover, experimental condition (describe prompt or explain prompt) was not related to causal learning score, non-causal learning score, or generalization. In subsequent analyses, therefore, we report performance as a function of designation (non-explainer or explainer) while also taking into account that older children were more likely to be designated as explainers than younger children, $\chi^2(1, N = 87) = 7.53$, $p = .006$.

Table 2
Study 2: Proportion of correct responses on each dependent measure by designation group and age group.

Designation	Age group	Causal choice task score	Color choice task score	Causal reconstruction score	Topper reconstruction score	Generalization function score
Nonexplainer	Younger	.23 (.06)	.53 (.09)	.37 (.09)	.40 (.09)	.47 (.09)
	Older	.74 (.17)	.42 (.12)	.37 (.11)	.58 (.11)	.68 (.11)
	Total	.43 (.07)	.49 (.07)	.37 (.07)	.47 (.07)	.55 (.07)
Explainer	Younger	.75 (.13)	.50 (.15)	.58 (.15)	.08 (.08)	.75 (.13)
	Older	.92 (.05)	.46 (.10)	.96 (.04)	.42 (.10)	.88 (.06)
	Total	.87 (.06)	.47 (.08)	.84 (.06)	.32 (.08)	.84 (.06)

Note. Standard errors of proportions are in parentheses.

Table 3
Study 2: Proportion of correct responses on each dependent measure by condition and age in years.

Condition	Age group	Causal choice task score	Color choice task score	Causal reconstruction score	Topper reconstruction score	Generalization function score
Nonexplainer	3 years	.10 (.07)	.55 (.11)	.25 (.10)	.30 (.11)	.50 (.12)
	4 years	.50 (.17)	.50 (.17)	.60 (.16)	.60 (.16)	.40 (.16)
	5 years	.75 (.13)	.42 (.15)	.42 (.15)	.50 (.15)	.58 (.15)
	6 years	.71 (.18)	.43 (.20)	.29 (.18)	.71 (.18)	.86 (.14)
	Total	.43 (.07)	.49 (.07)	.37 (.07)	.47 (.07)	.55 (.07)
Explainer	3 years	.67 (.33)	.33 (.33)	.33 (.33)	0	1.00
	4 years	.78 (.15)	.56 (.18)	.67 (.11)	.11 (.11)	.67 (.17)
	5 years	.83 (.11)	.42 (.15)	1.00	.33 (.14)	.83 (.11)
	6 years	1.00	.50 (.14)	.93 (.07)	.50 (.14)	.93 (.07)
	Total	.87 (.06)	.47 (.08)	.84 (.06)	.32 (.08)	.84 (.06)

Note. Standard errors of proportions are in parentheses.

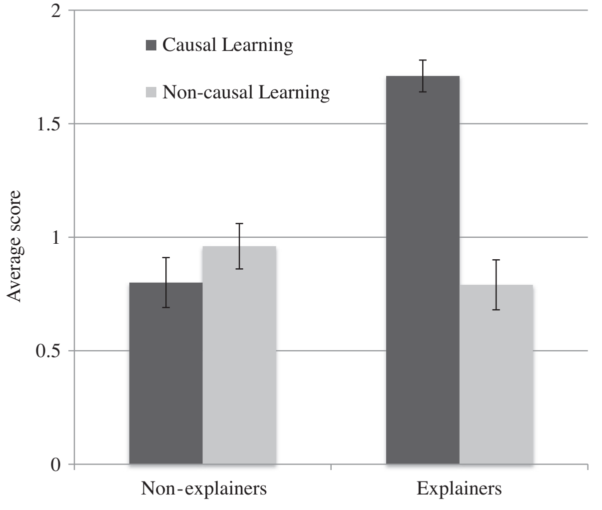

Fig. 3. Study 2: Causal and non-causal learning scores by designation.

Learning measures as a function of coded designation

A repeated-measures ANOVA with designation as a between-participants factor (explainer or non-explainer), age group as a between-participants factor (younger or older), and learning score as a within-participants factor (causal learning score or non-causal learning score) revealed the predicted interaction between designation and learning score, $F(1, 83) = 26.627$, $\eta_p^2 = .243$, $p < .001$. On measures of causal learning, children who explained ($M = 1.71$, $SD = .46$) outperformed those who did not ($M = .80$, $SD = .74$), $t(85) = 6.71$, $p < .001$ (Fig. 3). But on measures of non-causal learning, children who explained ($M = .79$, $SD = .66$) performed no better than those who did not ($M = .96$, $SD = .68$), $t(85) = -1.17$, $p = .25$ (Fig. 3). There was also a main effect of learning measure, $F(1, 83) = 15.762$, $\eta_p^2 = .16$, $p < .001$, with higher scores for causal learning ($M = 1.20$, $SD = .78$) than non-causal learning ($M = .89$, $SD = .67$); a main effect of designation, $F(1, 83) = 6.020$, $\eta_p^2 = .068$, $p = .016$, with higher scores for explainers ($M = 1.25$, $SD = .45$) than non-explainers ($M = .88$, $SD = .53$); and a main effect of age group, $F(1, 83) = 11.137$, $\eta_p^2 = .118$, $p = .001$, with older children ($M = 1.24$, $SD = .46$) outperforming younger children ($M = .82$, $SD = .50$).

Because older children were more likely than younger children to be designated as explainers, the preceding analysis potentially confounds designation with age. Therefore, we repeated the analysis within each age group to ensure that age did not drive the critical interaction between designation and learning measure. For the younger children, a repeated-measures ANOVA with designation (explainer or non-explainer) as a between-participants factor and learning measure (causal learning or non-causal learning) as a within-participants factor again revealed the predicted interaction between designation and learning measure, $F(1, 40) = 13.915$, $\eta_p^2 = .258$, $p = .001$, as did the equivalent analysis for older children, $F(1, 43) = 12.686$, $\eta_p^2 = .228$, $p = .001$. For older children, there was also a significant main effect of learning measure, $F(1, 43) = 19.358$, $\eta_p^2 = .310$, $p < .001$, with higher scores for causal learning ($M = 1.56$, $SD = .66$) than non-causal learning ($M = .93$, $SD = .65$), as well as a significant main effect of designation, $F(1, 43) = 6.422$, $\eta_p^2 = .130$, $p = .015$, with higher scores for explainers ($M = 1.38$, $SD = .36$) than non-explainers ($M = 1.05$, $SD = .52$).

Generalization as a function of designation

When analyzing generalization performance as a function of designation, explainers performed significantly better (32 of 38 succeeding) than non-explainers (27 of 49 succeeding), $\chi^2(1, N = 87) = 8.31$, $p = .004$. To test for differences across groups while accounting for the uneven distribution of ages across designations, we performed a logistic regression on generalization performance with age group entered in a first step and designation entered in a second step. This analysis revealed a significant effect of designation, $p = .023$ ($\beta = -1.25$, $SE = .55$), as well as a marginal effect of age group, with older children (36 of 45) more likely to succeed than younger children (23 of 42), $p = .072$ ($\beta = .917$, $SE = .51$).

Discussion

Our objective in Study 2 was to replicate and extend key findings from Study 1. First, we succeeded in finding reliable effects of explanation when comparing the content of children's responses rather than the experimental prompt that they received. As in Study 1, children who explained outperformed non-explainers on measures of causal learning but not on measures of non-causal learning. This result is important in establishing that effects of explanation do not derive solely from the use of language given that all children produced verbal responses. That effects of explanation were not eliminated when compared with alternative kinds of verbalization is especially striking in the context of our two studies given that the non-causal properties that we tested (e.g., color) were, if anything, easier to express linguistically than the causal properties (e.g., gear shape).

The verbal prompt conditions (explain prompt and describe prompt) were equally effective at prompting children to produce explanations. Thus, our analyses were based on the content of children's responses, and the effects of explanation in Study 2 are correlational. Nonetheless, our data demonstrate that children's explanatory responses are predictive of learning. The effects of the content of children's responses in Study 2 nicely complement the effects of prompted explanation in Study 1, as children's responses were elicited by general prompts to explain or describe (as opposed to the explicit questions about how the machine works used in Study 1). Across both studies, therefore, we have evidence for a causal relationship between explanation and learning (Study 1) that is mirrored in the content of children's responses (Studies 1 and 2).

General discussion

Our studies had three objectives: (a) to differentiate effects of explanation from those due to observation (Study 1) or verbalization (Study 2), (b) to examine whether and how prompts to explain selectively benefit young children's causal learning and may impair non-causal learning (Studies 1 and 2), and (c) to examine potential age-related differences in the effects of explanation on children's learning (Studies 1 and 2). In Study 1, children prompted to explain outperformed others on causal learning but not on memory for causally irrelevant details. In both Studies 1 and 2, children who provided an explanatory verbal response outperformed those who provided other verbal responses on measures of causal learning, but again this benefit did not extend to memory for causally irrelevant details. Notably, when it came to generalizing a function from one toy to another, explainers outperformed non-explainers. Thus, our data suggest that effects of explanation are distinct from those of observation or other kinds of verbalization and result in selective rather than general benefits for learning, even leading to impairments for younger children. In our task, explaining directed learners to functional–mechanical understanding but not to causally irrelevant details, a trend that was observed across age groups.

Why might explanation exert these selective effects? One possibility is that explanation is simply a constructive activity (Chi, 2009) or goal-directed activity (Nelson, 1973). We propose instead that although explanation likely recruits many cognitive processes that are shared with other kinds of constructive and goal-directed activities, explanation is especially conducive to causal learning and generalization. In the Introduction, we presented the hypothesis that explaining encourages learners to focus on causal mechanisms and generalization (Legare, 2012; Lombrozo, 2012; Williams & Lombrozo, 2013) precisely because invoking mechanisms and broad generalizations is characteristic of good explanations. Whereas other constructive and goal-directed activities may sometimes share these characteristics incidentally, they can also direct learners in a variety of alternative ways—depending on the nature of the task—and have consequences that are more or less diffuse.

In the Introduction, we also identified several ways in which effects of explanation could change during the course of early development. We found several age-related improvements in general performance, yet we observed only two developmental changes involving explanation. First, in Study 1, 3- and 4-year olds who were prompted to explain exhibited impairments when it came to non-causal learning, whereas 5-year-olds did not. This suggests that the beneficial effects of explanation do have an associated cost, but one that may be realized only on more difficult tasks or when cognitive resources are taxed. Second, in Study 2 (and to a lesser extent in Study 1), we found evidence that older children were more likely than younger children to generate verbal responses that were designated as explanations. Importantly, however, the beneficial effects of explanation did not interact with age. We suggest that older children are more likely to engage in explanation, both spontaneously and in response to prompts, but that effects of explanation are predominantly a function of the content and quality of the explanation rather than children's age.

Understanding the ways in which explanation does—and does not—improve learning speaks not only to questions about the development of causal knowledge but also to questions about how to most effectively harness explanation for use in educational interventions. For example, research with young children has shown that explanation benefits learning by increasing the efficiency of strategy use whether the children generated the explanation or learned the explanation from the experimenter (Crowley & Siegler, 1999). There is also evidence that generating both self-explanations and explanations to others (i.e., caretakers) improves problem-solving accuracy at posttest, with the greatest benefits for problem-solving transfer from explanations to caretakers (Rittle-Johnson et al., 2008). Our findings suggest that these effects may derive in part from the role of explanation in directing children toward causal regularities (in these cases involving reasoning and the application of problem-solving strategies) and that explanation can be less beneficial—and perhaps even harmful—when the target of learning is more perceptual or descriptive.

In educational research with adolescents and college students, learners who explain meaning in text either spontaneously or when prompted to do so understand more from the text and construct better mental models of the content (e.g., Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Chi, DeLeeuw, Chiu, & LaVancher, 1994; Magliano, Trabasso, & Graesser, 1999; Trabasso & Magliano, 1996). However, there are large individual differences in spontaneous engagement in self-explanation and in the quality of students' self-explanations. (e.g., Chi et al., 1989, 1994). Whereas a high-quality self-explanation would indicate an understanding of the meaning of the text, a low-quality self-explanation may involve description or restatement of the text. Across studies, we find similar variation in young children's verbal responses to both explicit and more general explanation prompts and demonstrate that the quality of verbal responses (i.e., presence of causal explanation) predicts learning outcomes.

Importantly, there is evidence that students can be trained to more effectively self-explain text and that the use of high-quality self-explanation strategies predict improved problem-solving performance (Bielaczyc, Pirolli, & Brown, 1995). For example, McNamara, O'Reilly, Rowe, Boonthum, and Levinstein (2007) demonstrated that self-explanation training improves reading comprehension to a greater extent than control tasks (i.e., reading out loud), and there is also evidence that self-explanation training increases engagement in elaboration, prediction, comprehension monitoring, the use of logic, and overall reading comprehension, particularly for students with lower prior content knowledge and for more difficult texts (McNamara, 2004; Ozuru, Briner, Best, & McNamara, 2010). Taken together, these studies provide evidence that self-explanation can be used productively as a learning strategy and that educational interventions can improve the quality of explanations. Our research provides evidence that analogous training methods may improve the quality of self-explanations in preschool-aged children. Our studies also suggest that the precise content of the explanation prompt can have an important influence on the content and quality of responses; although most children who were prompted to explain *how the machine works* in Study 1 produced a response coded as explanatory (38 of 48 children), a smaller proportion did so in Study 2 in response to the undirected prompt to *explain* the machine (17 of 41 children).

Finally, our findings that explanation can improve causal learning and foster generalization also bear on claims about the nature of development. A vast literature on development has challenged Piagetian claims that young children are limited to concrete appearances (Piaget, 1930), demonstrating instead that they recognize abstract relationships (e.g., Gopnik & Schulz, 2007) and unobserved properties (e.g., Gelman, 2003; Wellman & Gelman, 1992). Nonetheless, little is known about the mechanisms by which children succeed in going beyond appearances, as understanding causal function often requires (Sobel, Yoachim, Gopnik, Meltzoff, & Blumenthal, 2007). We propose that explanation may be an especially powerful tool for causal learning during early childhood precisely because its effects are relatively selective, orienting young learners toward causal mechanisms and promoting generalization.

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