

# First Contact: Children’s Emerging Sensitivity to Causality in Second-Order Learning

Ricky W.J. Choi

wonjoonc@andrew.cmu.edu  
Carnegie Mellon University

David H. Rakison

rakison@andrew.cmu.edu  
Carnegie Mellon University

## Abstract

The present study investigated young children’s causal generalizations by examining their inductions from second-order learning—where learned correlations between two pairs of features (A–B and A–C) are generalized to non-contiguous features (B–C). Specifically, we asked whether 3- to 6-year-olds could engage in such learning across two canonical causal event types—Blicket detector and Michottian launching—while manipulating contact as a perceptual cue for causality. We replicated Benton, Rakison, and Sobel (2021), finding that children consistently applied second-order learning to infer which objects would produce causal outcomes. Crucially, children’s responses did not differ overall between event types. However, there was a significant interaction by age and task condition: younger children learned better when objects did not contact, whereas older children learned better from contact events. Results are discussed with respect to implications for the development of children’s causal expectations.

**Keywords:** causal learning; causal perception; second-order learning; associative learning; child development

## Introduction

David Hume asserted that “instances, of which we have had no experience, must resemble those, of which we have had experience, and that the course of nature continues always uniformly the same” (Hume, 1779). Hume’s assertion underscores correlations as a fundamental informational basis for not only recognizing familiar patterns but also predicting novel occurrences in a world replete with relationships among objects, entities, and events. For example, things that have feathers tend to have wings, and this observation enables individuals to predict other features that constitute a bird; a spoon is likely to be found on a table next to a fork and knife to form cutlery arrangements; and the words ‘once upon’ reliably precede ‘a time’. These kinds of co-occurrences are found world-wide and repeat reliably in children’s daily lives (Tamis-LeMonda, Custode, Kuchirko, Escobar, & Lo, 2019; Turk-Browne, Scholl, Chun, & Johnson, 2009). Given this prevalence of correlational structure in the world, it is crucial to understand how the ability to encode these statistical patterns influences children’s learning over developmental time.

Considerable evidence shows that even newborn infants encode and learn correlations between features of objects and events in both artificial and naturalistic stimuli (Bulf, Johnson, & Valenza, 2011; Slater, Mattock, Brown, & Bremner, 1991). As infants develop, so does their capacity to process more complex correlations. By 8 months, they focus on discrete features (e.g., appearance, action, sound), but by 10–12 months, they recognize broader relations (Baumgartner & Oakes, 2011; Perone & Oakes, 2006). By 14 months, they link object parts and functions yet still encode correlations in-

discriminately, while by 18 months, they attend only to real-world-consistent correlations (Madole & Cohen, 1995).

These developmental changes in infants’ sensitivity to correlations suggest that the growing ability to process associations leads to changes in the basic elements for categorization: initially starting with discrete object features, then correlations among features, followed by correlations between functional properties and features (Madole & Cohen, 1995). Consequently, researchers have hypothesized that infants’ sensitivity to statistical regularities among features forms the basis for early representations of categories and concepts (Mareschal, Powell, Westermann, & Volein, 2005; Rakison & Lupyan, 2008; Unger & Fisher, 2021; Younger, 1990). These co-occurring features create mental associations, enabling infants to learn, for example, that feathers and wings or spoons and forks tend to co-occur.

Recognizing correlations is only part of the challenge, however; children must build comprehensive knowledge about the world from limited experiences. Despite their early sensitivity to statistical regularities in the world, children experience only a subset of all possible correlations in the world. Some theorists have argued that this limited exposure is insufficient to produce the conceptual and categorical knowledge that children acquire (Gopnik et al., 2004). For example, a child may encounter only a handful of dogs in the world: perhaps their family owns one, a neighbor has another, and they see a few more in the neighborhood. Yet, children can grasp the category of a dog and identify new, unfamiliar breeds with this small sample of observations (Quinn, Eimas, & Rosenkrantz, 1993). This ability is even more striking considering the variability within the category: breeds differ in size, color, type and length of fur, facial structure, and even the sound of their bark (for discussion on distributions of features see Mareschal, French, & Quinn, 2000). Given that children develop such rich categories despite limited experiences, children’s learning mechanism must go beyond recognizing only those correlations that they experience. This raises the question of what mechanism enables children to generalize from limited data to form such rich conceptual categories.

Traditional accounts of associative learning posit that associations can only be formed between cues that are physically present together. However, more recent work has shown that infants can associate memories of objects that were never shown together during training based on shared features (Cuevas, Rovee-Collier, & Learmonth, 2006; Rakison & Benton, 2019; Yermolayeva & Rakison, 2016). Researchers have referred to this ability to learn correlations between

features that have never been observed together as *second-order correlation learning* (hereon *second-order learning*). Yermolayeva and Rakison (2016) were the first to examine this phenomenon using an object-examination paradigm with infants. In their study, infants were introduced to a series of objects that shared certain body types and external parts, presented one at a time; then, during the test phase, infants encountered novel objects that combined these features in either consistent or inconsistent ways. Remarkably, infants as young as 7 months demonstrated learning of these second-order correlations between the static object features and the body to which they should be attached.

This ability to learn associations among features that never directly co-occur has been argued to be critical for more complex cognitive development, such as semantic organization and language acquisition. For instance, a domain-general associative mechanism can support flexible representations of knowledge, enabling children to detect clusters of reliably co-occurring features that define taxonomic categories (e.g., “apple” and “spaghetti” do not co-occur with each other, but each separately co-occur with “eat”) (Unger, Savic, & Sloutsky, 2020). Similarly, Sloutsky, Yim, Yao, and Dennis (2017) showed that children can infer that a novel word like “dax” refers to an animal when it is presented alongside words associated with animals (e.g., “furry” and “zoo”), illustrating how sensitivity to indirect connections helps learners expand both semantic knowledge and vocabulary without direct exposure to every possible pairing.

Children’s ability to infer associations between features not experienced together may also provide a basis for interpreting causal relationships. Indeed, cause-and-effect inferences frequently arise from partial evidence, where relevant information is separated in time or only indirectly related (e.g., a child infers that medication causes recovery after observing their parent both take the medication and later recover, despite never directly seeing medication immediately produce recovery). This suggests that children’s capacity to integrate widely dispersed correlational information is especially important in the causal domain. To investigate whether young learners can form causal inferences from such indirectly related information, Benton et al. (2021) explored whether 2- and 3-year-old children can engage in second-order learning to produce causal inferences in a version of the Blicket detector event (Gopnik & Sobel, 2000; Griffiths, Sobel, Tenenbaum, & Gopnik, 2011). In the classic Blicket detector event, participants are introduced to a novel machine called the “blicket detector” and are told that it activates when “blickets” are placed on it but not when other non-blickets are placed on it. Children are then asked to figure out which objects are blickets based on different patterns of evidence. Research that employed the Blicket detector event has shown that causal reasoning emerges and develops between 18 months and 5 years of age (Gopnik, Sobel, Schulz, & Glymour, 2001; Sobel & Kirkham, 2006).

Benton et al. (2021) first showed children two different ob-

jects, each with a distinct internal feature (e.g., a red square with an internal purple diamond and a green cylinder with an internal yellow circle). Next, the children observed that a red square without the internal feature caused a novel machine to change colors when it came into contact with it, whereas a green cylinder without the internal feature did not cause any change. Finally, the children were asked to indicate which of two novel objects—a blue triangle with an internal purple diamond and a blue triangle with an internal yellow circle—would activate the machine.

The researchers reasoned that if children could engage in second-order learning to make causal inferences, they would choose the new object with the purple diamond because that shape was initially connected to the red square that activated the machine. Indeed, the results showed that 2- and 3-year-old children consistently chose the object with the purple diamond, which suggests that second-order learning extends to causal reasoning involving abstract associations. A subsequent connectionist computational model demonstrated that the ability to use second-order learning—constrained by information-processing capacity—is sufficient to make causal inferences in this task (Benton et al., 2021).

Although Benton et al. (2021) suggested that children interpret second-order correlations causally, inferring a causal outcome alone does not confirm that children represent events as causal or are sensitive to causal structure. Two requirements must be met to establish that children interpret and represent a given event as causal. First, children must make relevant inferences based on the properties of the entities in the event. Second, they must distinguish between causal events and perceptually similar but non-causal events and produce inferences based on the event’s causal status. Although Benton et al. (2021) explored the first criterion by showing that children can make inductions from second-order correlations, they did not address whether children make diverging inductions from causal and non-causal events, when both contain identical correlational information. This distinction is crucial because a causal interpretation, as opposed to an associative one, predicts that inferences will diverge for events that share the same correlational structure but differ in causal status. Therefore, it remains unanswered whether inferences arising from second-order learning are sensitive to the causal status of given events. Furthermore, the Blicket detector event is not the only way to examine how children reason about causality; examining whether these inferences generalize across multiple event types provides a more robust test of children’s causal learning in diverse contexts.

The following experiment was designed with two aims. The first aim was to provide a conceptual replication of Benton et al. (2021) to confirm that young children can engage in second-order learning with both Michottian launching events (Michotte, 1963) and Blicket detector events (Gopnik & Sobel, 2000). The addition of Michottian launching events is significant because the present experiment, for the first time, compares causal learning for two traditional causal

event types in developmental research (Gopnik & Sobel, 2000; Michotte, 1963). Second, it investigated whether children’s second-order learning is sensitive to the causal status of events; that is, do they treat the same correlational information differently depending on whether the event includes causal or non-causal information? This issue was examined by manipulating the presence or absence of contact—and thus the appearance of causality—between objects. Although contact is not a necessary feature for causation, research shows that infants, young children, and adults reliably use spatial contiguity as a perceptual cue for interpreting causation (Gopnik & Sobel, 2000; Leslie, 1984; Michotte, 1963; Rolfs, Dambacher, & Cavanagh, 2013). Thus, we tested a within-subjects contrast, comparing inference from “causal” events that included object contact with “non-causal” events where contact was absent. For example, if children infer that a purple diamond causes the activation of a machine, is their learning process sensitive to whether there was contact—a perceptual cue for causal status—in the initial association between the red square and the machine’s activation?

## Experiment

The participant age range replicated Benton et al. (2021) and included older children to investigate second-order correlation learning beyond three years of age. All task events contained objects that were unique geometric shapes with discriminable colors chosen via Colorgical (Gramazio, Laidlaw, & Schloss, 2017), but the events differed in whether contact was present between two objects before state changes occurred in the Blicket detector condition and an object launched in the Michottian launching condition.

### Method

**Subjects** 51 3- to 6-year-old (30 boys and 21 girls;  $M_{\text{age}} = 54.86$  months,  $SD = 11.34$  months, range = 35 – 76) children were recruited from the Children’s School at Carnegie Mellon University. Power analysis indicated that this sample provided 86% power to detect the second-order learning performance reported in Benton et al. (2021).

**Stimuli** All stimuli were created using Blender 4.1.0 and Microsoft PowerPoint. The stimuli were presented on and the data were recorded with PsychoPy (Peirce et al., 2019) on a 13-inch Apple MacBook Air. This experiment used a digital version of the Blicket detector event (Gopnik & Sobel, 2000) and Michottian launching event (Michotte, 1963).

**Procedure** The experiment took place in a lab room, with participants seated ~30cm from a 30x21cm LCD screen. An experimenter, seated beside the participant, controlled the task via an external mouse.

All participants completed two sessions, each with a warm-up match-to-sample task and two experimental tasks (total four tasks: detector-contact, detector-gap, launching-contact, and launching-gap). The four tasks differed by the type of event (Blicket Detector or Michottian launching) and the task condition (contact or spatial gap condition), and consisted of

two training trials and a test phase. The order of these tasks within sessions was counterbalanced using a Latin square.

In the detector-contact task, an object descended 388 pixels and made contact with a stair-shaped object, triggering a color change (oscillating between gray and blue) and a ringing sound for 3.5 seconds. In the detector-gap task, the same state changes occurred without contact, as the object hovered over the stair shape. In the launching-contact task, one object traveled 640 pixels from the left and made contact with a stationary center object, triggering the latter to move rightward with a 3.5-second gong sound. In the launching-gap task, the second object began moving despite a spatial gap between it and the first. Object identities (e.g., shape, color) were fully counterbalanced to control for feature-driven biases. See Figure 1 for a visual overview.

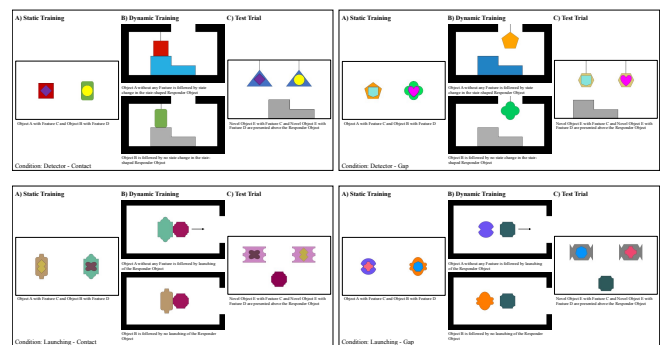


Figure 1: Design of Experiment 1. Children were tested in one of four conditions: Detector – Contact (top left), Detector – Gap (top right), Launching – Contact (bottom left), and Launching – Gap (bottom right).

**Training Trials** In the static training trial, participants were first shown two objects—such as a red square and a green cylinder—positioned side by side on the screen. Each object had a distinct internal feature (e.g., the red square had a purple diamond; the green cylinder had a yellow circle). Both objects were displayed simultaneously, and the sequence was repeated twice. The position of the objects on the screen (i.e., left or right) was counterbalanced across participants.

In the dynamic training trial, participants were introduced to three new objects. The trial began with a novel object positioned at the bottom of the screen for Blicket Detector events, or at the center of the screen for Michottian Launching events (hereon the responder object for both events). Two additional objects, identical to those used in static training but without internal features (e.g., a red square and a green cylinder), participated in a sequence of movements toward the responder object. First, the red square moved toward the responder object, traveling a set distance and coming to a stationary position. After this object stopped moving, the responder object underwent a state change lasting 2.5 seconds. After the state change, the red square returned to its original off-screen position. Next, the green cylinder moved the same distance toward the responder object. Then, it remained stationary for

2.5 seconds, failing to induce any state change before moving back to its original off-screen position.

**Test Trials** In all test trials, three objects were presented side by side; two objects were novel (e.g., a blue triangle with a purple diamond and a blue triangle with a yellow circle) and the third object was identical to the responder object from the dynamic training trial. Both novel objects had the same internal features that were paired with objects during the static training trial (e.g., blue triangle with purple diamond and blue triangle with yellow circle). The experimenter then pointed at the responder object and said, “Here are two new toys. Can you tell me which toy will set this off?” This task phrasing was chosen to be consistent with that of Gopnik and Sobel (2000). If children associated the red square with the purple diamond during static training and then linked the red square (without its internal feature) to the responder object’s state change during dynamic training, they should choose the novel object containing the purple diamond to activate the responder object during the test phase. If children failed to encode either association, they should be at chance in choosing the novel object containing the purple diamond to activate the responder object. However, if children misremembered and encoded flipped associations—for example, associating the red square with the yellow circle—their selection of the novel object with the yellow circle would still indicate second-order learning. In other words, second-order learning does not depend on the precise encoding of specific associations but rather on the ability to generalize whatever associations are encoded, regardless of their accuracy.

After the training and test trials were completed, all children were then given four memory checks. In two of the memory checks, children were shown the static phase objects and internal features and were asked to place the internal features on the objects to which they were initially presented with. In the other two memory checks, children were shown the objects without internal features and asked to indicate which object was followed by a state change.

## Results

Participants’ choice between the two test trial objects for each event were treated as the primary binary dependent measure. All analyses were conducted in R 4.4.1 using the ‘lme4’, ‘performance’, and ‘effectsize’ packages in addition to the base ‘stats’ package (Bates, Mächler, Bolker, & Walker, 2015; Ben-Shachar, Lüdtke, & Makowski, 2020; Lüdtke, Ben-Shachar, Patil, Waggoner, & Makowski, 2021).

Before children’s test trial response performance was analyzed, the response data was processed accounting for their memory check results. This contextual processing was necessary to evaluate children’s task responses not only based on their binary choices in isolation but also conditional on the associations that the children encoded during the training trials. For instance, if the child incorrectly learned a flipped association (e.g., learning an association between a red square and a yellow circle when the red square was paired with a purple

diamond in training), their task response cannot be evaluated solely based on the normative choice. Essentially, the child is given credit for responding based on what they encoded, even if their encoding was wrong. This ensures that the response evaluation reflects children’s mental representations of the task. Table 1 shows children’s test trial responses before and after data processing.

Table 1: Children’s raw and processed responses according to remembered associations (D: Blicket Detector; L: Michottian Launching).

Event	Raw		Processed	
	Correct	Incorrect	Correct	Incorrect
D-Contact	20	21	29	12
L-Contact	29	13	30	12
D-Gap	27	16	34	9
L-Gap	19	24	27	16

Preliminary analyses showed that neither children’s gender nor any of the counterbalancing measures (task event type order, stimuli condition, and task condition order) was significantly related to children’s test trial choice, all  $p$ -values  $> 0.997$ . Thus, we collapsed over these variables.

Children’s test trial responses were evaluated based on whether they were consistent with each child’s encoded associations and second-order learning. A binomial test showed that children were more than twice as likely to choose the test object consistent with second-order learning than the inconsistent object (odds ratio = 2.449; 120 of 169;  $p < 0.001$ ; 95% CI [0.635, 0.777]). Additionally, a binomial test conducted for each of the four tasks revealed that children’s responses in each task were above chance to choose the consistent test object (see Table 2 for binomial test results).

Table 2: Binomial Test Across Tasks (D: Blicket Detector; L: Michottian Launching).

Event	Frequency	ORs	Probability	$p$ -value
D-Contact	29 of 41	2.413	0.707	0.011
L-Contact	30 of 42	2.185	0.714	0.008
D-Gap	34 of 43	3.367	0.791	0.0001
L-Gap	27 of 43	1.500	0.628	0.126

We next examined the main hypotheses related to the effects of event type (Blicket detector vs. Michottian launching) and task condition (contact vs. gap) on children’s test trial responses. Data were entered into a mixed-effects logistic regression including fixed effects for age (mean-centered), task condition (contact or gap, mean-centered), event types (detector or launching), warm-up trials (mean-centered), and the two memory check types (memory checks of static and dynamic training). The predictor variables were mean-centered to facilitate the interpretation of the model es-

timates. We also included an interaction between age, task condition, and event type, and a separate interaction between the two memory check types. The model accounted for random intercepts for individual participants to account for variability in children’s baseline responses.

The mixed-effects regression model found no main effect of age, task condition, or event type, all  $p$ -values  $> 0.231$ , but yielded a significant intercept (standardized  $\beta = 3.44$  [1.93, 6.10],  $SE = 1.01$ ,  $p < 0.001$ ) and an interaction effect between age and task condition (standardized  $\beta = 1.58$  [1.00, 2.50],  $SE = 0.37$ ,  $p = 0.049$ ), which was qualified by a likelihood ratio test comparing against a reduced model without the interaction,  $\chi^2(1) = 4.183$ ,  $p = 0.041$ . Figure 2 illustrates the interaction effects of task condition (contact or gap) and children’s age in months (mean-centered,  $M_{\text{age}} = 54.86$  months) on the predicted probability of choosing the test object consistent with second-order learning. The interaction between age and task condition suggests a developmental change in children’s second-order learning. In the gap events, younger children exhibited a higher probability of task responses consistent with second-order learning, but this probability declined with age. Conversely, the probability of a consistent response increased with age for the contact events, such that older children were more likely than younger children to engage in second-order learning.

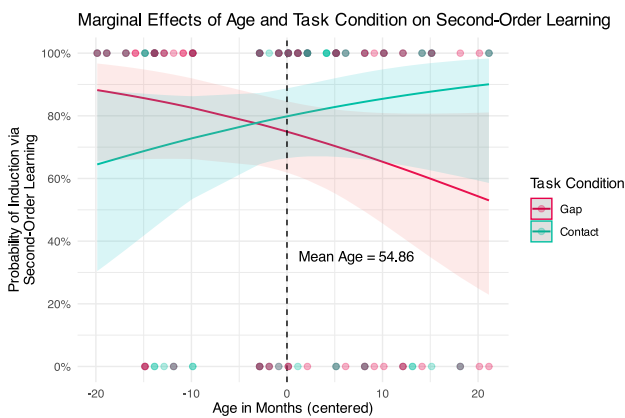


Figure 2: Marginal Effects of the Interaction Between Age and Task Condition on Second-Order Learning.

## Discussion

The results of this experiment revealed that children between three and six years of age were significantly above chance when making responses consistent with the second-order correlations presented during training. Overall, children’s responses were not significantly affected by task condition (e.g., whether the red square made contact with the responder object or not), or event type (Michottian launching vs. Blicket detector).

These findings replicate the overall pattern reported by Benton et al. (2021), providing converging evidence that children can engage in second-order learning with Blicket de-

tector events. Furthermore, children not only succeeded in producing inductions consistent with second-order learning in the Blicket detector events, but they also did so in Michottian launching events.

Michottian launching and Blicket detector events differ in the literature by the kind of causal learning they are used to study; perception versus inference or reasoning. However, these two types of events need not be treated as mutually exclusive because children’s understanding of causality likely involves both perceptual and inferential processes. However, past research has not addressed whether children’s learning is differentially affected in the presence of Michottian launching versus Blicket detector events. If there were such differences, this would have been reflected in the current study in children’s ability to engage in second-order learning in the two causal contexts. In the present study, children engaged in second-order learning in both event types. Therefore, children’s learning is suggested to be consistent across these causal events, enabling children to extract and generalize associations across various causal events in the world.

Although children’s responses did not show an independent effect of task condition, there was a significant interaction between age and task condition on their likelihood of making choices consistent with second-order learning. Specifically, younger children’s learning was facilitated in events with spatial gaps between objects, which have typically been interpreted as non-causal by infants in previous work with Michottian launching events and by preschoolers in Blicket detector studies (Gopnik & Sobel, 2000; Leslie, 1984; Michotte, 1963). In contrast, older children showed enhanced learning in events with direct contact between objects, which are generally treated as causal events by children from three years of age (Gopnik & Sobel, 2000).

This result may appear to contradict findings from works showing that even young infants perceive contact—but not non-contact—as causal, particularly in launching events (Cohen & Oakes, 1993; Kominsky & Carey, 2024). However, it is crucial to distinguish between causal perception and causal reasoning. While infants may possess the former competence, this does not necessitate that causal perception is the input to children’s inductive process. Causal perception is the output to be explained and not an input to causal induction (Ichien & Cheng, 2022). Indeed, the present findings suggest that although perceptual sensitivity to contact may be present early in life, its influence on learning and induction strengthens over development as attentional constraints and experience-based expectations become more prominent.

Young children’s success in gap trials is not surprising given that even seven-month-olds can engage in inductions via second-order learning (Yermolayeva & Rakison, 2016). Moreover, younger children’s weaker performance on contact trials aligns with Benton et al. (2021), who proposed that two-year-olds fail to produce inferences consistent with second-order correlations in contact-based Blicket detector events due to limited information-processing capacity.

What is striking is the crossover trajectory in children's inductive behavior across the conditions. In principle, if children's inductions (as seen here and in Benton et al., 2021) were purely associative, there would be no behavioral difference between contact and gap conditions—both share identical correlational information. Alternatively, if children's inductive process were domain-specific to causal reasoning, we would expect chance-level or lower performance in the gap condition and above-chance performance with contact. Yet the data do not align with either view because children show neither identical performance across conditions nor selective above-chance performance for contact events. However, the observed trajectory suggests that a domain-general associative learning mechanism can yield inductive generalizations that are increasingly sensitive to causal status.

One question arising from this result is why spatial contiguity influences children's learning so strongly. Spatial contiguity may affect how learners segment and encode the interaction, ultimately shaping the inductive process. Zacks, Swallow, Vettel, and McAvoy (2006) discuss how coarse-grained boundaries in visual events, where objects are clearly separated, elicit stronger brain responses in the MT+ and pSTS regions. This suggests that gap events may be processed more readily by younger children, owing to more distinct segmentations of object motion. Such visual processing may influence children's learning because contact events may not be sufficiently represented and encoded to be integrated in younger children's inductive processes.

Children's experiences with physical causality may also shape their developing sensitivity to contact-based learning. As children accumulate real-world experiences with causal interactions—like kicking a soccer ball—they form stronger expectations about how objects typically behave upon contact. This enhanced expectation, in turn, guides children's selective attention and improves children's processing of contact events. This developmental trajectory of children's attention in learning has been observed in studies exploring the development of children's eye movements, category learning, and the formation of self-propelled motion concepts (Cicchino, Aslin, & Rakison, 2011; Helo, Pannasch, Sirri, & Rämä, 2014; Wan & Sloutsky, 2024). These findings suggest that as children accumulate experiences with causal interactions in their environment, they become increasingly sensitive to contact as the deterministic feature of physical causal events. This heightened sensitivity then leads to a greater likelihood of producing a generalized induction.

These findings align with past work that suggests a gradual shift from reliance on perceptual features to more complex relational and conceptual associations in infants' and young children's learning (Mandler & McDonough, 1998; Rakison, 2006; Ralston & Sloutsky, 2023). Specifically, the results support the claim that this developmental trajectory emerges due to a process called "constrained attentional associative learning" (Rakison, 2005; Rakison & Lupyan, 2008). According to this view, infants and young children initially

struggle to attend to complex relations because of limited memory, encoding, and information-processing capacities. As these capacities improve, children become able to encode a wider range of complex relations, but their attention remains relatively unconstrained. Over time, repeated experiences with relations in the real world strengthen particular associative links, and consequently, children's attention becomes focused on these strengthened relations.

According to this account, younger children—whose attention is less constrained by prior experiences—are more likely to form associations based on perceptual features rather than selectively forming associations based on causal relations. Consequently, they can engage in second-order learning when causal cues are absent. However, they are less likely to engage in second-order learning when causal cues involve physical contact because such events require greater information-processing capacity. As children's information-processing capacities improve, they become better able to encode the more complex events involving contact. Their attention becomes constrained by strengthened associations with causal cues like physical contact—because such events are prevalent in the real world—making them more sensitive to these cues and enhancing learning when such cues are present.

Looking ahead, several directions for future research emerge from this study. First, exploring the developmental trajectory of children's causal inductions across a broader age range—including younger as well as older children—would offer a more comprehensive account of how sensitivity to causal cues develops. Second, the present findings raise the possibility that different causal schemas (e.g., contact causality) may emerge at different developmental periods, suggesting that some causal expectations stabilize earlier than others. Finally, developing computational models to simulate the gradual shift of children's sensitivity toward contact (and away from gap) during second-order learning could offer theoretical insights into the mechanisms driving the transition.

## Conclusion

This study constitutes one of the first systematic attempts at examining young children's inductions in the context of multiple causal event types while manipulating contact as a cue for causality. The established consensus has been that causal reasoning in children emerges and develops between 18 months and 5 years of age, but little work has explored the exact nature of this developmental transition. This experiment advances a novel account of how children's ability to reason about causes develops over time. Specifically, it suggests that this transition is driven by the gradual emergence of top-down expectations of physical causal events, which increasingly shapes children's attention during learning. As a result, their inductive processes become selectively sensitive to diagnostic causal cues—such as contact—allowing children to focus on these features and strengthen their capacity to generalize associations in a broad range of causal contexts.

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