Don’t throw the associative baby out with the Bayesian bathwater: Children are more associative when reasoning retrospectively under information processing demands

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Abstract

Causal reasoning is a fundamental cognitive ability that enables humans to learn about the complex interactions in the world around them. However, the mechanisms that underpin causal reasoning are not well understood. For example, it remains unresolved whether children's causal inferences are best explained by Bayesian inference or associative learning. The two experiments and computational models reported here were designed to examine whether 5- and 6-year-old will retrospectively reevaluate objects—that is, adjust their beliefs about the causal status of some objects presented at an earlier point in time based on the observed causal status of other objects presented at a later point in time—when asked to reason about 3 and 4 objects and under varying degrees of information processing demands. Additionally, the experiments and models were designed to determine whether children’s retrospective reevaluations were best explained by associative learning, Bayesian inference, or some combination of both. The results indicated that participants retrospectively reevaluated under minimal information-processing demands (Experiment 1) but failed to do so under greater information processing demands (Experiment 2) and that their performance was best captured by associative learning with only minimal support for Bayesian inference.

Keywords: causal reasoning; cognitive mechanisms; computational models; associative learning; Bayesian inference

Few capacities are more important than the ability to reason and make inferences about causal relations. Causal reasoning enables human learners to make predictions and inferences (e.g., Bullock, et al., 1982; Shultz, 1982), to intervene on those relations to generate new effects (e.g., Butler et al., 2020; Schulz et al., 2007), and to reason about counterfactual claims—both about what might have been and how events could have turned out differently (e.g., Harris et al, 1996; Walker & Nyhout, 2020). These, and many other studies (e.g., Bonawitz & Lombrozo, 2012; Gopnik et al., 2001; Legare et al., 2010; Meltzoff et al., 2012; Walker & Gopnik, 2014), posit that young children have sophisticated causal reasoning capacities.

A fundamental question that underlies this research is *how* children make such inferences. One answer to this question is that children’s causal inferences are best described by Bayesian inference. Although this view is often described as a computational level of analysis (cf. Marr, 1982), some advocates suggest that children use cognitive mechanisms that approximate or even represent Bayesian calculations (Bonawitz et al., 2014; Xu, 2019; see also Griffiths et al., 2015). Causal reasoning starts with statistical learning capacities that are present in infancy (e.g., Gomez, 2002; Kirkham et al., 2002; Marcus et al., 1999; Saffran et al., 1996) but that develop into a system that infers abstract patterns of coherent causal structure from probabilistic data (Gopnik & Wellman, 2012; Weisberg & Sobel, 2022).

An alternative perspective is that associative learning alone is sufficient to describe children’s causal inferences. On this view, children build up a representation of causal structure from connecting and processing multiple associative relations and statistical regularities. Connectionist models—which learn largely via associative learning—have provided a proof of concept that causal learning can emerge from such associative processes (e.g., Benton et al., 2021; McClelland & Thompson, 2007). Additionally, comparative investigation between non-human animals and adults (e.g., Heyes, 2012) and studies of instrumental action and conditioning on human infants (e.g., Greco et al., 1990; Rovee-Collier, 1999) provide behavioral support for associative learning as a candidate mechanism for how children reason in the world.

One way to illustrate the tension between these hypotheses in development is through investigations of retrospective reasoning, such as *backwards blocking* (Shanks, 1985). This is a form of reasoning that involves reevaluating the causal status of an ambiguous event based on learning more about the status of other unambiguous events (see also De Houwer et al, 2002; Larkin et al, 1998; Kruschke & Blair, 2000; Lovibond, 2003; Van Hamme & Wasserman, 1994, for other work on adults). One of the first studies to examine backwards blocking reasoning in children was carried out by Sobel et al. (2004). They introduced 3- and 4-year-olds to a machine called a “blicket detector” that lit up and played music when certain objects called “blickets” were placed on it (Gopnik & Sobel, 2000). Children were then shown that two novel objects, A and B, activated the machine when they were placed on it at the same time. Children were then shown that object A alone either did or did not activate the machine. On both types of trials, children were then asked whether each object was a blicket. Children judged that A was a blicket only when it activated the machine. Their judgments of object B also differed across these conditions. Children judged object B more likely to be a blicket when object A failed to activate the machine than when it did so. Using modified procedures, toddlers and even infants as young as 8 months showed a similar pattern of responses (Sobel & Kirkham, 2006).

These findings—and specifically the finding that children’s causal inferences are sensitive to base rates (e.g., Sobel et al., 2004, Exp. 3)—have been interpreted as support for a Bayesian description of causal reasoning rather than a description that appears more to associative learning. This is because some associative models (e.g., Rescorla & Wagner, 1972) predict that the strength between object B and the machine’s activation is equivalent between the backwards blocking (where A is effective) and another trial in which A is not effective (labeled indirect screening-off trials). Moreover, even a modified version of the Rescorla-Wagner model (e.g., Van Hamme & Wasserman, 1994) does not predict differences in such reasoning when the base rates of the causal effectiveness of an object is manipulated.

There are, however, two facets of these data that warrant further consideration. First, McCormack et al. (2009) questioned what exactly was being reevaluated in a backwards blocking inference. They showed 4- and 5-year-olds two objects (A and B) that activated the machine together, and then that object A activated the machine alone. They compared children’s causal status judgments for object B with a sequence in which a third object (C), unrelated to the compound set, activated the machine (i.e., AB+, C+). The 4-year-olds did not differ in their judgments (although 5-year-olds did, judging B less likely to be efficacious than C). This control measure—which we adopt here—is a superior measure of assessing whether children reevaluate their causal judgments, and specifically of examining whether children reevaluate the causal status of the object(s) shown independently or the object only shown as part of the initial ambiguous data.

Second, although there are investigations suggesting Bayesian models are a better account for children's retrospective reasoning (Griffiths et al., 2011; Sobel et al., 2004), these investigations focus on a simplified case - reasoning about exactly two candidate causes. Indeed, when three candidate causes are presented, some of children’s inferences are better explained by Bayesian models, while other inferences are better explained by associative reasoning (Griffiths et al., 2011; Experiment 3). This suggests an intriguing possibility: as the number of candidate causes increases, children might not use more rational reasoning measures, and instead default back to simpler, more associative mechanisms (akin to System 1/System 2 reasoning, Evans, 2003, 2011; Kahneman, 2011).But why are associative mechanisms simpler in this case? A fundamental difference between these two modeling approaches is the way a hypothesis space is initially constructed. Some associative models (including the one we instantiate here) posit a linear increase in the complexity of the hypothesis space based on the number of potential causes. That is, as the number of potential causes moves from 2 to n, the complexity of the hypotheses under consideration increases linearly from 2 to n as children must keep track of an associative value between each candidate cause and the effect. In contrast, Bayesian models (as we will instantiate below) increase the complexity of the hypothesis space exponentially as the number of candidate causes increases. For example, if each object can either be a blicket or not and children are asked to reason about two potential blickets, then children would need to determine which of 2­2 or 4 causal hypotheses is correct. If, instead, children are asked to reason about four blickets, then the space increases to 16 (i.e., 2­4) potential hypotheses. Between just these two scenarios the child must consider up to four times as many causal hypotheses. Thus, if children are sensitive to this increase in the size of the underlying hypothesis space and they possess limited information-processing abilities, then they might be expected to rely on simpler modes of processing that are better captured by associative processes than on more sophisticated forms of thinking that approximate Bayesian inference.

The present study presents children with different kinds of retrospective causal inferences that increase the information processing demands by asking them to reason about more than two objects at a given time. This procedure allows us to consider not only more generalized examples of retrospective causal inference, but also by presenting model fits from both associative learning and Bayesian accounts, we can explicitly contrast whether each model explains all facets or different facets of the results. Unlike previous cases where Bayesian inference more clearly describes children’s reasoning, here we hypothesize that both modeling approaches will have distinct explanatory power, even if there is a tendency for children to rely more on one process (e.g., associative learning) than another given the increase in the demands placed on children’s information-processing abilities relative to other studies on this topic.

There is now considerable evidence demonstrating that children do default to simpler modes of thinking when their information-processing abilities are taxed (e.g., Doebel & Zelazo, 2015; Frye et al., 1995; Zelazo et al., 1996; Zelazo et al., 2003). For example, recently Kenderla and Kibbe (2023) demonstrated that 8- and 10-year-old children showed decreased reliance on working memory and greater dependence on manual exploration during a challenging virtual memory game. The goal of this game was to find three cards with shared and differing features. Given that children were not required to maintain information in memory when manually exploring, manual exploration ostensibly was a less cognitively effortful strategy than one that required an already resource-limited system such as working memory. Similarly, Richland et al. (2006) found that 3- and 4-year-old children made more featural and relational errors when asked to reason about multiple relations or when the task included a salient distractor than when asked to reason about a single relation without a distractor.

Even in infancy there is development from more associative to more rational inferences. Using an anticipatory eye-gaze measure, Sobel and Kirkham (2007) found that 8-month-olds exhibited backwards blocking inferences similar to preschoolers, but 5-month-olds’ inferences were more associative in nature. When infants make judgments about the reliability of others’ information, their decision-making seems to be best explained by associative processing (Sobel et al., 2020; Tummeltshammer et al., 2014). As children enter the preschool years, those judgments become more rational in nature (Sobel & Kushnir, 2013), although occasionally they will default to associative forms of processing, particularly under information processing demands (e.g., Hermes et al., 2018; Luchkina et al., 2020). Further, on other kinds of retrospective reasoning tasks, as the information demands of the procedure increase, only older children between the ages of 3-7 succeed (Fernbach et al., 2012; Erb & Sobel, 2014; Sobel et al., 2017). Finally, beyond explicit causal reasoning tasks, preschoolers’ performance on theory-of-mind and social-problem-solving tasks was adversely affected when they first completed tasks that taxed their information-processing abilities compared to when such capacities were not taxed (Caporaso & Marcovitch, 2021; Powell & Carey, 2017; Steinbeis, 2018). Considered together, these studies indicate that although children use different reasoning processes under different information-processing demands; the higher those demands, the simpler the process (e.g., Cohen, 1988).

In the present study, we considered how children made retrospective inferences when first shown ambiguous data (i.e., three objects together produce an effect), followed by further evidence involving one of those objects (Experiment 1) or two of those objects (Experiment 2). In both cases, the logic of our design followed McCormack et al. (2009), in which we contrasted these retrospective inferences with control trials in which children saw the same initial ambiguous data, and then unrelated objects that had similar efficacy. The question across both experiments is the extent to which children show qualitative evidence for a Bayesian description of their causal inference, but an overall stronger fit of associative reasoning. After presenting these behavioral data across two experiments, we present a pair of computational models to illuminate possible cognitive mechanisms by which children arrived at their causal judgements.

**Experiment 1**

Five- and 6-year-olds observed three objects (A, B, and C) together cause a machine to activate. Then they observed that object A either caused (backwards blocking trials) or failed (indirect screening-off trials) to cause the machine to activate by itself. They were then asked whether each object individually caused the machine to activate. These experimental trials were compared to control trials in which children observed three different objects (A’, B’ and C’) activate the machine together (i.e., the same as the initial data point in the experimental trials), followed by a fourth object (D), which either did (Backwards Blocking control) or did not (Indirect Screening Off Condition) make the machine activate.

A retrospective inference is defined as treating objects A’, B’ and C’ in the control trials differently from objects B and C in the experimental trials. Because object D in the control trials was not shown in conjunction with any other objects, its efficacy should have no bearing on the causal status of any other object. However, because object A in the experimental trials was initially shown in conjunction with B and C, and then its efficacy was demonstrated unambiguously, retrospective inferences involve changing beliefs about the efficacy of the other objects, relative to the objects in the control trials. Because McCormack et al. (2009) found that 5 and 6-year-olds made such retrospective inferences about two candidate causes, we have decided to test the same-age children.

**Method**

**Participants.** Participants were 32 5-year-olds (16 boys and 16 girls; *M* = 64.81 months, range = 60-71 months, SD = 3.48) and 31 6-year-olds (17 boys and 15 girls; *M* = 77.81 months, range = 72-83 months, SD = 3.78). Sample size was determined based on previous studies on backwards blocking reasoning in human children (e.g., Griffiths et al., 2011; Sobel et al., 2004). Two children were excluded from analysis for failing to participate (*N* = 1) or missing video (which made coding their responses impossible) (*N* = 1). We did not collect demographic information about the sample, but the demographic information about sample of children collected by the laboratory during this time was as follows: 82% White/Caucasian, 3% Black/African American (9%), 4% Asian/Asian American (4%), 0.5% Native American (1%), and 11% of Mixed Descent (3%). Sixteen percent identified as Hispanic/Latinx (compared with 17% of the population). Similarly, the overall household income level of families tested in the lab during this time was as follows: Less than 30K: 7%, 30-50K: 7%, 50-70K: 14%, 70-90K: 9%, 90-120K: 25%, Over 120K: 38%. The median income for the population as measured by the 2020 Census was ~$74K.

**Materials.** The “device” used in the current study was a computer-animated version of the blicket detector (Gopnik & Sobel, 2000). The device was a white rectangle with a black border that measured 5.99 cm × 23.47 cm and that was presented on a computer screen. If the device was “on”, the white region of the rectangle turned blue when objects touched it. If the device was “off”, the white region remained white. A maximum of 4 differently colored circles were shown on the screen. Each circle measured 2.67 cm × 2.67 cm (see Figure 1 below). The machine was designed such that it activated immediately when the bottommost edge of a circle—predetermined to be a blicket—contacted it. At the start of any given trial, three or four equally spaced circles appeared above the machine. Finally, the videos contained a built-in script, which experimenters, but not the study participants, read. All video events were created in Microsoft PowerPoint.

**Procedure.** All study procedures were reviewed and approved by the University’s Institutional Review Board, and parental informed consent was obtained before each experimental session. Participants were tested in a quiet room in a local children’s museum. At the beginning of the experiment, all participants were shown a pretraining video. The video consisted of a rectangular base (i.e., the previously mentioned “blicket detector”) and two shapes (i.e., a gray triangle and a gray pentagon). Crucially, these shapes were unrelated to the circles used during the experimental portion of the experiment. The pretraining phase began with the triangle (object A) and pentagon (object B) next to each other above the machine. Object A then descended until it contacted the machine, which immediately activated (i.e., the white region changed from white to blue). Object A then returned to its starting position above the machine. Object B then descended until it contacted and failed to activate the machine. Object B then returned to its starting position. Finally, both objects descended until they contacted and activated the machine. Participants were then asked whether each object was a blicket. This event ensured that participants understood the task and recognized that individual objects could activate the machine and that it activated if at least one effective object was placed on it.

Following this pretraining phase, participants were given four trials. Half the participants received two backwards blocking experimental trials and two backwards blocking control trials. The other half received two indirect screening-off experimental and two indirect screening-off control trials. The order of these trials within each condition was counterbalanced using a Latin square design. Different colored objects were used across all trials to prevent carryover effects. A schematic of this procedure is shown in Figure 1. Finally, all study responses were coded offline after each study session. Although study responses were coded offline, an experimenter was present throughout an entire study session.

Diagram

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Figure 1. Schematic of a Backwards Blocking experimental trial. The upper-right portion of the figure shows the backwards blocking event as it unfolded across time. The lower-left portion of the figure shows the three objects and the text, “Is this one a blicket?” above each object across time.

**Backwards Blocking Experimental and Control Trials.** The two backwards blocking experimental trials began with three differently colored objects, which were located above the machine. The text, “Look, I have these three toys. Let’s find the blickets. Watch what happens” appeared above the objects. All three objects (i.e., objects A, B, and C) then descended until they contacted and activated the machine. At this point, the text, “Look, these also make the machine go!” appeared above the objects. The objects then returned to their starting positions.

The left- or right-most (counterbalanced) object (which we will refer to here as object A) then descended until it contacted and immediately activated the machine. The text, “Look, this one makes the machine go!” then appeared above the objects. This object then returned to its starting position. Children were then asked whether each object was a blicket. Specifically, the text, “Is this one a blicket?” with a downward-facing arrow then appeared above each object, and participants were asked to indicate whether each object was a blicket. Children received two of these trials, which were identical except for the color of the objects.

The two backwards blocking control trials began with four differently colored objects (i.e., objects A, B, C, and D), which were located above the machine. Objects A, B, and C then descended until they contacted and activated the machine; object D remained in place while objects A-C descended onto the machine. Object D then descended by itself until it contacted and activated the machine. The left-right position of object D was counterbalanced. Children were then asked whether each object was a blicket. Children once again received two trials, which were identical except for the color of the objects.

**Indirect Screening-Off Experimental and Control Trials.** The procedures for the indirect screening-off experimental and control conditions were identical to the backwards blocking trials except that object A (experimental trials) and D (control trials) failed to activate the machine. Table 1 below illustrates the key trial structures for the backwards blocking and indirect screening-off conditions in Experiments 1 and 2.

|  |  |  |
| --- | --- | --- |
| Condition | First learning phase | Second learning phase |
| Backwards blocking (experimental) | ABC+ | A+ |
| Backwards blocking (control) | ABC+ | D+ |
| Indirect screening-off (experimental) | ABC+ | A- |
| Indirect screening-off (control) | ABC+ | D- |

Table 1. Schematic of the task structure for the backwards blocking and indirect screening-off experimental and control trials.

**Results**

Figure 2 shows participants’ responses to “Is this a blicket” for each object. Participants’ yes/no responses were treated as a primary binary dependent measure. Data were entered into a five-way mixed-effects logistic regression with Age as a continuous fixed effect, Condition (Backwards blocking vs. Indirect screening-off) as the between-participants fixed effect, Trial Type (Experimental vs. Control), Objects (A vs. B vs. C vs. D), and Trial Number (Trial 1 vs. Trial 2) as the within-participants fixed effects, and participant as the random effect. This analysis yielded several experimental-effects and two-way interactions, which were qualified by a single three-way interaction among Condition, Trial Type, and Object, χ*2*(2) = 64.85, *p <* .001.

To unpack the nature of the interaction among Condition, Trial Type, and Object, we ran separate two-way binomial mixed-effects models separately for the backwards blocking and indirect screening-off conditions, with Trial Type (Experimental vs. Control) and Objects (A vs. B vs. C vs. D) as the within-participants fixed effects and participant as the random effect. This analysis revealed a main effect of Trial Type, *χ2*(1) = 9.62, *p* = .002 and an interaction between Trial Type and Objects, χ*2*(2) = 16.38, *p* < .001. To explore this interaction, we constructed a set of one-way binomial mixed-effects models for the experimental and control trials within the backwards blocking condition. The Objects factor was treated as the sole within-participants fixed effect in these follow-up analyses. Participants were once again treated as a random effect to control for the within-participant variance from multiple responses. The one-way binomial model for the control trials within the backwards blocking condition did not reveal a significant effect of Objects,χ2(3) = 1.33, *p* = .72. This means that participants treated the objects similarly in the control trials of the backwards blocking condition. In contrast, the second one-way linear model for the experimental trials within the backwards blocking condition revealed a significant experimental effect of Objects, χ2(2) = 19.29, *p* < .001. This experimental effect reflected the fact that participants judged object A as a blicket more often than object B, odds ratio = 204.79, 95%CI [33.96, 4609.11], *p* < .001, and object C, odds ratio = 129.67, 95%CI [18.75, 2824.63], *p* < .001. However, participants treated objects B and C equivalently, odds ratio = 1.58, 95%CI [0.62, 4.19], *p* < .001.

The two-way mixed-effects logistic regressions for the indirect screening-off condition also revealed a main effect of Trial Type, *χ2*(1) = 26.91, *p* < .001, a main effect of Objects, *χ2*(3) = 67.32, *p* < .001, and an interaction between Trial Type and Objects, *χ2*(2) = 19.59, *p* < .001. To explore this interaction, we constructed a set of one-way mixed-effects regressions for the experimental and control trials within the indirect screening-off condition. The two one-way mixed-effects regressions for the experimental and control trials revealed a significant experimental effect of Objects, both χ*2*-values > 36.78, both *p*-values < .001. In the experimental trials, participants judged object A as a blicket less often than any of the other objects, all odds ratios < 0.07, all *p*-values < .001. Likewise, in the control trial, participants considered object D to be less likely to be a blicket than any of the other objects, all odds ratios < 0.06, all *p*-values < .001. No other differences reached statistical significance.

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Figure 2. The counts of participants’ responses to whether each object was a blicket across the conditions and trial types. Bars show standard error.

**Evidence of retrospective reasoning.** To examine whether participants engaged in backwards blocking reasoning, data for the experimental and control trials within the backwards blocking condition were entered into a two-way mixed-effects logistic regression with Trial Type and Object as the within-participants fixed effects and participants as the random effect. This analysis revealed only a main effect of Trial Type, *χ2*(1) = 17., *p* < .001. This result indicated that participants did engage in backwards blocking reasoning. In particular, a follow-up, one-way binomial mixed-effects model showed that participants were less likely to consider the objects whose efficacy were not shown individually in the experimental trial (i.e., objects B and C) to be blickets than the objects that were placed on the machine together in the control trial (i.e., objects A’, B’, and C’), odds ratio = 0.19, 95% CI [0.09, 0.78], *p* < .001.

We also ran the same analysis as above, but this time for the indirect screening-off condition. Although this analysis also revealed a main effect of Trial Type, *χ2*(1) = 4.39, *p* = .04, a follow-up one-way mixed-effects logistic regression indicated that participants’ treated the objects that did not participate on the machine in the experimental trials (i.e., objects B and C) and the objects that did not participate on the machine in the control trials (i.e., objects A, B, and C) equivalently, odds ratio = 0.50, 95%CI [0.25, 1.01], *p* = .051.

**Discussion**

In the experimental trials of Experiment 1, children were shown three objects that together activated a machine and then shown that one of those objects was or was not effective on its own. When that object was effective, children reevaluated the efficacy of the other two objects: They stated that they were less likely to be effective than objects in a control condition in which a fourth, unrelated object was effective. When that object was not effective, children did not retrospectively reevaluate the efficacy of the other objects and judged the objects equivalently across both conditions.

Before discussing the different mechanisms that might describe these data, we wanted to consider a second, related retrospective inference. In Experiment 1, following the ABC+ event participants were either shown an A+ event (in the backwards blocking condition) or an A- event (in the indirect screening-off condition). Experiment 2 was similar to Experiment 1 except for what children observed following the ABC+ events during what is sometimes referred to as the second learning phase (e.g., McCormack et al., 2009). In the experimental trial in the backwards blocking condition, they observed an AB+ event during the second learning phase; in the control trial in the same condition, children observed a DE+ event during the second learning phase. Children in the indirect screening-off condition were shown the same series of events except that the machine did not activate. If children’s ability to engage in various forms of retrospective reevaluation is related to their information processing, in Experiment 2 children should be less likely to engage in retrospective reevaluation than children in Experiment 1.

**Experiment 2**

Experiment 2 was similar to Experiment 1 except for the number of objects that were placed on the machine during the second part of the experimental trials. In the experimental trial, children were shown that three objects activated the machine together, and then two of those three objects either did so or did not. These data were compared with a control trial in which three different objects activated the machine, and then two additional novel objects either did or did not activate the machine in tandem.

**Method**

**Participants.** Participants were 32 five-year-olds (18 boys and 14 girls; *M* = 65.31 months, range = 60-75 months, SD = 3.65) and 32 six-year-olds (10 boys and 22 girls; *M* = 76.56 months, range = 65-83 months, SD = 4.33). Participants were recruited in the same manner as Experiment 1. Participants were 12% Asian/Asian American, 9% Black/African American, 10% Hispanic, and 69% White/Caucasian.

**Materials and Procedure.** The materials and procedure for Experiment 2 were identical to that for Experiment 1 with the following exceptions: During the backwards blocking experimental events following an event in which objects A, B, and C together activated the machine, two objects A and B descended onto and subsequently caused the machine to activate. Likewise, during the backwards blocking control events which consisted of 5 objects (i.e., objects A-E), objects D and E descended onto and subsequently caused the machine to activate. Objects D and E did not descend onto the machine during the initial event in which A, B, and C activated the machine and in this way were unrelated to objects A, B, and C. The indirect screening-off experimental and control trials were identical to the backwards blocking trials except that the machine neither activated when objects A and B descended onto it in the experimental trial nor when objects D and E descended onto it during the control trial. The left- and right-most positions of objects A and B during the experimental trial and objects D and E during the control trial were counterbalanced. Table 2 below shows the structure of the events used in Experiment 2.

|  |  |  |
| --- | --- | --- |
| Condition | First learning phase | Second learning phase |
| Backwards blocking (experimental) | ABC+ | AB+ |
| Backwards blocking (control) | ABC+ | DE+ |
| Indirect screening-off (experimental) | ABC+ | AB- |
| Indirect screening-off (control) | ABC+ | DE- |

Table 2. Schematic of the task structure for the backwards blocking and indirect screening-off experimental and control trials.

**Results**

Figure 3 shows participants’ responses to “Is this a blicket” for each object. Data were entered into a five-way mixed-effects logistic regression model with Age as a continuous fixed effect, Condition (Backwards blocking vs. Indirect screening-off) as the between-participants fixed effect, Trial Type (Experimental vs. Control), Objects (A vs. B vs. C vs. D), and Trial Number (Trial 1 vs. Trial 2) as the within-participants fixed effects, and participant as the random effect. This analysis only yielded a main effect of Trial Type, χ*2*(1) = 14.33, *p =* .04. This reflected that fact that across the backwards blocking and indirect screening-off conditions, participants were less likely to treat the objects in the experimental trial as blickets than objects in the control trial, odds ratio = 0.45, 95%CI [0.33, 0.62], *p* < .001.

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Figure 3. The counts of participants’ responses to whether each object was a blicket across the conditions and trial types. Bars show standard error.

**Evidence of retrospective reasoning.** We next examined whether participants engaged in retrospective reasoning using the operationalization of it from Experiment 1. Data were entered into a two-way mixed-effects logistic regression with Trial Type and Object as the within-participants fixed effects and participants as the random effect. This analysis did not reveal any main effects or interactions, all χ*2*-values < 1.91, all *p*-values > .18. The same picture emerged for the indirect screening-off condition—this analysis did not reveal any main effects or interactions, all χ*2*-values < 1.79, all *p*-values > .41. Thus, unlike Experiment 1, there was no evidence that participants engaged in backwards blocking reasoning. This finding is likely the result of the increased demand on children’s information processing abilities: Children were not only required to reason about 3 and 4 objects (as in Experiment 1), but they were also required to reason about 2 rather than 1 object during the second learning phase in the backwards blocking and indirect screening-off conditions.

**Discussion**

Unlike Experiment 1, in Experiment there was no evidence that children engaged in retrospective reasoning. Specifically, children treated the objects equivalently between the experimental and control trials. In the next section, we present fits from two computational models to determine whether an associative mechanism, a Bayesian mechanism, or some combination of both best captures children’s judgements across Experiments 1 and 2.

**Computational Models**

We fit two computational models to the behavioral data. The first was a model based on Bayesian inference. This model was described initially by Sobel et al. (2004) and in more detail in Griffiths et al. (2011). The second was a simple connectionist model, trained with the Delta Rule (Widrow & Hoff, 1960).

**Bayesian Model.** The Bayesian model starts with a set of hypotheses *H*. Each hypothesis *h* ∈ *H* is assigned a *prior probability*, *p*(*h*), which indicates the initial belief that a learner has in a particular hypothesis prior to seeing data. After the learner observes data, *d*, the learner computes a posterior probability, *p*(*h*|*d*), given an updated belief about each hypothesis, given the data. This is done using Bayes’ rule, shown in Equation 1:

(1)

In this formula, *p*(*d | h*) is the probability of the data *d* under a particular hypothesis *h* (also known as the *likelihood*).

Forming the initial hypothesis space relies on assuming that there is a set of objects *O* and a detector d, such that any object *o* ∈ *O* can potentially cause the detector *d* to activate. Given that participants are shown that the machine activates when objects with the label “blicket” are placed on its surface, a hypothesis *h* corresponds to a structure that posits whether individual objects have the causal effectiveness to activate the detector (see Griffiths & Tenenbaum, 2005, for more computational details). Griffiths et al. (2011) describe the formal parameterization of this hypothesis space and model that results in the hypothesis space shown in Figure 3.

To instantiate the model, each hypothesis is given a prior probability *p*(*h*), which is a function of the child’s belief about the base rate of blickets *ρ*. This prior corresponds to the number of blickets posited by the hypothesis. For example, in the figure, Hypothesis 0 posits 3 blickets, so its *p*(*h*) = *ρ*3. Hypotheses 1, 2, and 4 posit exactly 2 blickets, so their *p*(*h*) = *ρ*2(1−*ρ*). Hypotheses 3, 5, and 6 each posit 1, which makes their *p*(*h*) = *ρ*(1−*ρ*)2. Finally, Hypothesis 7 posits no blickets, which makes its *p*(*h*) = (1-*ρ*)3.

**Timeline

Description automatically generated with medium confidence**

Figure 3. The eight different causal hypotheses indicating the possible causal relations for a causal event that involves three objects and one blicket detector. *A*, *B*, and *C* correspond to the three objects that were used on the machine and *E* indicates the activation of the machine.

For the purposes of this demonstration, we will assume that the model itself assumes that objects with causal efficacy will act deterministically on detectors.[[1]](#footnote-1) As a result, the likelihood of each hypothesis is equal to 1 if that hypothesis could produce the data and 0 if not. This allows each model to be updated based on Bayes’ rule given the data. The way the model determines the probability that an object is a blicket is based on the posterior probability of the models in the hypothesis space; that is, the probability that any object *o* is a blicket given the data *d* can be calculated by the equation in (2)

where *p*(*o*→*E* | *h*) is 1 if there is an edge between that object and the detector in h, and 0 otherwise.

Crucially, because the predictions of this (or any) Bayesian model will depend on the prior probability that any given object is a blicket, we fit a Bayesian model with the following prior probabilities: .5, .65, .8, .95, and 1. We considered a range of prior probabilities because it was unclear what participants’ baseline assumptions were about the prior probability of blickets in the absence of explicit manipulations to those probabilities. Thus, by deriving the model’s predictions for various prior probabilities, it was possible to compare the model’s predictions for the different probabilities to children’s actual treatment of the objects. The best quantitative fit of this model to the data in Experiments 1 and 2 is shown below in Table 3.

**Connectionist model**. We also built a set of two-layer connectionist models. One set of these models corresponded to Experiment 1 and the other set corresponded to Experiment 2. The model architecture for the Experiment 1 simulations is shown in Figure 4. The rationale for building only a two-layer model was to explore whether a simple learning model trained with the Delta Rule (Kruschke, 1992; Widrow & Hoff, 1960)—which is formally equivalent to the traditional Rescorla-Wagner model (Danks, 2003; Gluck & Bower, 1988)—could be used to explain these data. Similar to children, we trained 16 models (i.e., ‘participants’) per condition for both experiments (i.e., 32 total model runs for Experiment 1 and 32 total model runs for Experiment 2), and like the children, each model received two trials. Each new participant began with a fresh set of small random weights (sampled uniformly between ±0.1). Finally, data were aggregated over the responses of each model to allow us to fit the model's responses to participants' count data (as shown in Figures 2 and 3).

The input layer for the model consisted of four units for Experiment 1 (corresponding to the four objects) and five units for Experiment 2 (corresponding to the five objects), and the output layer consisted of a single unit for the simulation of both experiments (corresponding to the activation of the machine). When object was placed on the machine, the activation value of its corresponding input unit was set to a value of 1 (and 0 otherwise). The input units could not take on any other values beside 0 or 1. If an object that was a blicket was placed on the machine, then the model was trained to turn on the single output unit (i.e., to produce an activation of 1).

All simulations used a learning rate of .05 but no momentum. Model weights were initialized to small random values (distribution range = ± 0.1), and the output units used sum-squared activation functions. The activation of the single output unit was interpreted as the model’s confidence (or prediction) that a given object was a blicket and could range between 0 and 1 due to the sigmoid activation function (unlike the input units, whose input values were “hard clamped” or fixed).

A diagram of a machine

Description automatically generated  
Figure 4. The connectionist model used to simulate Experiment 1.

Turning on the first three input units simulated placing objects A, B, and C on the machine, and training the model to turn on the single output unit corresponded to teaching the model that the machine activated when objects A-C were placed on it. During the subsequent A+ trials in Experiment 1 or the AB+ trials in Experiment 2, only the first input unit (for the simulation of Experiment 1) or the first and second input units (for the simulation of Experiment 2) were turned on, but again the model’s task was to activate the single output unit. The backwards blocking control trials were identical to the experimental trials except that the fourth input unit (corresponding to object D in Experiment 1) or the fourth and fifth input units (corresponding to objects D and E in Experiment 2) were turned on following the ABC+ trial. The indirect screening off experimental and control trials were identical to the backwards blocking experimental and control trials except that the model was trained to turn off the single output unit (i.e., to produce an output activation of 0) during the A- and D- phases of the indirect screening-off experimental and control trials. Each phase of the simulations—which were shown twice to be consistent with the behavioral study—lasted anywhere between 200 and 1,000 epochs. This meant that one complete simulation lasted anywhere between 800 (i.e., 200 × 4) and 4,000 (i.e., 1,000 × 4) epochs. Networks were trained for different numbers of epochs to ensure that the model-fit results were not idiosyncratic to the precise number of training epochs. Below we show the quantitative fit of this model to the data in Experiments 1 and 2. The best quantitative fit of this model to the data in Experiments 1 and 2 is also shown below in Table 3.

**Results**

To assess the quantitative fit of the predictions of the connectionist and Bayesian models to the data, we computed the root mean square (RMSE) and mean absolute error (MAE) between each model’s predictions (for the connectionist model these were the average activation of the single output unit in response to each object; for the Bayesian model these were point estimates) and participants’ mean responses to the objects across Experiments 1 and 2. One or both metrics have been used in previous simulation studies to assess a model’s quantitative fit to behavioral data (e.g., Bhat et al., 2022; Buss & Spencer, 2014; Spencer et al., 2022; Steyvers et al., 2003; Stojnic et al., 2023). Lower values on each metric indicate better model fit. Table 1 below shows the model fits for the different connectionist and Bayesian model instantiations across both experiments and for different subsets of the data (e.g. model fit to the data overall, to the backwards blocking data only, etc.).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| (A) Model fit to the data overall | | | | | | | |
| Experiment 1 | | | | Experiment 2 | | | |
| Connectionist‡ | | Bayesian Model | | Connectionist‡ | | Bayesian Model | |
| RMSE | MAE | RMSE | MAE | RMSE | MAE | RMSE | MAE |
| .15 | .11 | .17 | .17 | .13 | .11 | .16 | .13 |
|  |  |  |  |  |  |  |  |
| (B) Model fit to the backwards blocking data only | | | | | | | |
| Experiment 1 | | | | Experiment 2 | | | |
| Connectionist‡ | | Bayesian Model | | Connectionist‡ | | Bayesian Model | |
| RMSE | MAE | RMSE | MAE | RMSE | MAE | RMSE | MAE |
| .19 | .16 | .20 | .18 | .13 | .11 | .15 | .14 |
|  |  |  |  |  |  |  |  |
| (C) Model fit to the indirect screening-off data only | | | | | | | |
| Experiment 1 | | | | Experiment 2 | | | |
| Connectionist‡ | | Bayesian Model | | Connectionist | | Bayesian Model‡ | |
| RMSE | MAE | RMSE | MAE | RMSE | MAE | RMSE | MAE |
| .08 | .07 | .18 | .16 | .11 | .11 | .12 | .03 |
|  |  |  |  |  |  |  |  |
| (D) Model fit to the experimental trials only | | | | | | | |
| Experiment 1 | | | | Experiment 2 | | | |
| Connectionist | | Bayesian Model | | Connectionist | | Bayesian Model‡ | |
| RMSE | MAE | RMSE | MAE | RMSE | MAE | RMSE | MAE |
| .19 | .16 | .19 | .16 | .16 | .14 | .14 | .12 |
|  |  |  |  |  |  |  |  |
| (E) Model fit to the control trials only | | | | | | | |
| Experiment 1 | | | | Experiment 2 | | | |
| Connectionist‡ | | Bayesian Model | | Connectionist‡ | | Bayesian Model | |
| RMSE | MAE | RMSE | MAE | RMSE | MAE | RMSE | MAE |
| .10 | .08 | .20 | .17 | .11 | .09 | .17 | .17 |

Table 3. Model fit indices for the various models and instantiations for the data overall and the data for the backwards blocking, indirect screening-off, experimental, and control trials in Experiments 1 and 2 data. ‡ Corresponds to the best fitting overall model based on average RMSE and MAE.

The main finding from Table 3 is that, although the Bayesian model outperformed the connectionist model in 2 situations and exhibited comparable performance in 1 situation, the connectionist model generally performed better than the Bayesian model (achieving better fits to the data in 7 of the 10 situations). These findings suggest that participants may simultaneously be relying on associative processing and Bayesian inference, even when there is a greater tendency to rely on associative learning to reason about multiple potential causes. Stated somewhat differently, these data neither clearly support the conclusion that children rely exclusively on Bayesian inference to reason about retrospective inference, nor do they permit the conclusion that children rely exclusively on associative learning about such inferences. Instead, these data support the conclusion that children weigh these two cognitive mechanisms differently depending on the number of potential causes about which they are asked to reason. Bayesian inference may be given more weight than associative learning when there are a small number of potential causes (such as in Sobel et al., 2004), but as the number of causes and the information processing demands of the task increase participants may give more weight to associative learning (such as in the current study).

**General Discussion**

The purpose of this study was to examine whether and how children engage in retrospective reasoning under more strenuous information processing demands, in which children must track the efficacy of more than two objects. Data for Experiment 1 indicated that when shown first that three objects activated a machine together, and then that one of those objects did so individually, the other two objects were judged as less likely to be efficacious than analogous objects in a control condition. When the individual object did not activate the machine on their own, judgments of the efficacy of the other objects were not different from the control condition. However, in Experiment 2 when two of the three objects were revealed to together activate or not activate the machine subsequently, children did not show evidence of retrospective inference in either type of trial.

We subsequently fit a Bayesian model and a connectionist model to the data from both experiments. The Bayesian model did make some qualitative predictions about retrospective reevaluation that were seen in children’s responses in Experiment 1 but not Experiment 2. However, overall, the connectionist model tended to provide better fits across the trials and experiments. In contrast to findings where children only must reason about two objects, increasing the demand characteristics of the experiment caused children default to a more associative strategy. This was especially true in Experiment 2 where the information demands were even greater than that in Experiment 1.

The value of the connectionist model is that it provided a plausible account of the nature of children’s associative processing in the current study. This can be seen perhaps most clearly when one considers how the model arrived at its judgements for the objects in the control trial in the backwards blocking condition. For example, when the model saw three objects activate the machine together and then a fourth do so independently, it arrived at its causal judgements based on a relatively simple counting strategy. During the simulation of this trial, when all four objects were first presented to the model, the resulting difference at the output layer between the activation of the single output unit and the predicted activation of that unit was equivalent for all four objects. Thus, because the difference between the observed and predicted activation of the output unit was equivalent for all four objects, the model made equivalent weight adjustments in sign and magnitude to the connections between each object and the output unit. Crucially, these connections instantiated each object’s association with the machine’s activation. As such, because objects A-D were shown with the “machine’s activation” (i.e., the output unit = 1) an equal number of times, the strength of the association between each object and the machine’s activation was equivalent. Given that the connectionist model provided a better fit overall (and in various specific places) than the Bayesian model, it seems likely that children also (mostly) relied on a similar associative based counting procedure.

In contrast, the Bayesian model predicted a clear difference between the causal effectiveness of the first three objects and the fourth object. Because the fourth object was placed on the machine by itself, its causal status as an effective object is unambiguous and should be high. In contrast, when all children know is that three objects activate the machine together, the only conclusion they can come to is that at least one of the other three objects have efficacy. A Bayesian model predicts that the probability that each is efficacious is greater than the base rate, but not necessarily at ceiling. Whereas the Bayesian model made qualitative predictions about retrospective reevaluation in the experimental trials that were mostly upheld (at least in Experiment 1), children made closer to ceiling-level responses in the control trials (particularly in Experiment 2).

What accounted for why children engaged in retrospective reevaluation in Experiment 1 but not in Experiment 2? The current study suggests that when tasks exceed children’s information-processing abilities, they will resort to less sophisticated strategies and cognitive mechanisms such as associative learning (e.g., Cohen et al., 2002), even though multiple processes (in this case, associative learning and Bayesian inference) may be simultaneously in operation but to different degrees.

Before closing, some potential criticisms are worth noting. First, in the present study, children’s reasoning overall was more consistent with an associative model than one that is described by Bayesian inference. Yet that does not mean that Bayesian models could not explain the data under some circumstances. For instance, one of the pieces of evidence for a Bayesian description of causal inference is that children are sensitive to and make different inferences about the base rates of causal properties (e.g., Griffiths et al., 2011; Sobel et al., 2004; Sobel & Munro, 2009). Here, we did not present children with base rates prior to their making an inference. If we were to have done so, and in the case where the base rate of object’s efficacy was rare, children might be cued not to use an associative counting strategy, even given multiple potential causes. In other words, their inferences about unambiguous data (i.e., individual objects that specifically do or do not activate the machine) should be unchanged, but other inferences about ambiguous data might be different. Although we can think of modifications to our associative model, which could theoretically consider such base rate data, the simple connectionist model that we used to simulate the data here would be less explanatory than the Bayesian model we present.

A second criticism concerns the artificial nature of the paradigm used here, which was necessitated by the COVID-19 pandemic. Testing remotely on a computer screen may have introduced a level of noise in the data that is fundamentally different than testing in person with real objects. Future studies should replicate our study. If such a study revealed that participants performed more normatively than associatively in person, this would suggest that children’s normative inferences may not be as robust as originally thought—it is present when tested in person but nearly absent when tested on a computer. Such a finding would be interesting regardless because it would add nuance to the literature on children’s causal inferences.

A third criticism concerns the logic behind our model fitting. Our model fits were based on aggregating a group of children’s yes/no responses and fitting those averages to a model’s stochastic predictions. Previous studies on children’s causal inferences used such an approach. Studies with adults, however, asked them to make more graded inferences (e.g., rate on a scale of 1-10 how likely a particular object caused the machine to activate). Given that we investigated a slightly older sample than some other studies of retrospective reasoning in children, such a graded response measure could be used in a reproduction of these studies. This could further help distinguish between the qualitative predictions of each model and the quantitative model fits.

A fourth potential criticism concerns the absence of developmental change in children’s retrospective reevaluations: Children’s backwards blocking and indirect screening-off inferences were unrelated to age in both experiments. Although we failed to observe an age effect, the current results do have developmental implications. If we are correct that children resort to more associative forms of processing when their information-processing abilities are stretched, then these results suggests that if younger children are tested in a replication of the current study their inferences should be even more associative than the 5- and 6-year-olds tested here. This is because younger children presumably possess less robust information-processing abilities than older children and thus should be more affected by the increase in the number of objects used (relative to past studies on retrospective reevaluation) than the 5- and 6-year-olds tested here. Conversely, if children older than that tested here or even adults are tested in a replication of the current study, then not only should they be less affected by the increase in the number of objects presumably because they possess more information-processing abilities than the children tested here, but their inferences should also better align with the predictions of the Bayesian model than the associative model. Although it remains to be seen whether these predictions will hold in younger children, recent data by Benton and Rakison (2023) do support these predictions: In a study that was similar in many ways to the current one—including in the use of three and four objects—adults’ backwards blocking inferences better aligned with Bayesian processes than associative ones. When one considers this finding given the current results, a clearer developmental picture emerges. Together, they not only suggest that cognitive processing evolves from a more associative approach in younger children to a more Bayesian-oriented strategy in adults but that this developmental shift may be supported by increases in underlying information-processing. Nonetheless, future research will want to test younger children than that tested here to better assess the viability of the current information-processing account.

**Conclusion**

This study constitutes one of the first systematic attempts to examine retrospective reasoning in human children in the context of multiple candidate causes. A longstanding view has been that the cognitive mechanism by which people reason about causal events is Bayesian inference rather than associative processes. The experiments reported here support a different conclusion: Under information processing demands, children rely more on associative learning than Bayesian inference.

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1. The Griffiths et al. (2011) model assumes that this can be learned through a hierarchical process, and there have been other ways this model has been refined (see e.g., Goodman et al., 2011; Ullman & Tenenbaum, 2020); we are presenting a simpler model for the purposes of this investigation. [↑](#footnote-ref-1)