Don’t throw the (associative-learning) baby out with the bathwater just yet: Backwards-blocking reasoning with *multiple* potential causes in human children

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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 available evidence suggests that the mechanism or set of mechanisms that underpin causal reasoning are not well understood. It is unclear, for example, whether causal reasoning is underpinned by a Bayesian mechanism, an associative mechanism, or both. Some theorists have argued that a Bayesian mechanism underpins causal reasoning because it can better account for backward-blocking and indirect screening-off findings in children and adults (e.g., Sobel, Tenenbaum, & Gopnik, 2004). However, the evidence is mixed about the extent to which learners engage in both kinds of reasoning. Here, we report three experiments that examine to what extent adults engage in backwards blocking and IS reasoning using the blicket-detector design (e.g., Gopnik et al., 2001), what mechanism best explains their behavior in this task, and under what conditions are adults’ causal ratings consistent with the predictions of the three competing computational and analytical models. The results of Experiment 1 revealed that adults’ causal ratings in the backwards-blocking condition (as well as in the indirect screening-off condition) were consistent with the predictions of the traditional and modified Rescorla-Wagner models when asked to reason about two objects. The results of the present study suggest that adults use associative processes to reason about two objects but a Bayesian-inference-like process to reason about three or more objects.

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

Few capacities are more important than the ability to reason and make inferences about cause-and-effect relations. Causal reasoning enables human learners to make predictions and inferences (e.g., Bullock, et al., 1982; Leslie & Keeble, 1987; Oakes & Cohen, 1990; Shultz, 1982), to intervene on those relations to generate new effects (e.g., Butler et al., 2020; Gopnik et al., 2001; 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; Sobel, 2004; Walker & Nyhout, 2020). These and many other studies (e.g., Bonawitz & Lombrozo, 2012; Gopnik et al., 2001; Legare et al., 2010; Meltzoff et al., 2014; Walker & Gopnik, 2014) posit that young children have sophisticated causal reasoning capacities.

A fundamental question that underlies this research is *how*—that is, by what cognitive mechanism or mechanisms—children make such inferences. One answer to this question is that children’s causal inferences are underpinned by a Bayesian-inference mechanism that is in place early in development. The crux of this idea is that learners use a simple form of Bayes’ rule to reason about causal events and to choose the causal hypothesis—among potentially infinitely many causal hypotheses—that is most consistent with the observed data (e.g., Bonawitz et al., 2014; Gopnik & Wellman, 2012; Griffiths & Tenenbaum, 2005, 2007; Xu, 2019). Crucially, causal reasoning starts with statistical learning capacities that are present in infancy (e.g., Gomez, 2002; Johnson et al., 2006; 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.

An alternative perspective is that associative learning alone is sufficient to explain children’s causal inferences. Connectionist accounts of causal reasoning (e.g., Rogers & McClelland, 2004), 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) suggest that associative processing is 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 *backwards blocking* (Shanks, 1985). This is a retrospective inference in which learners reevaluate 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 et al., 2003; Van Hamme & Wasserman, 1994, for other work on adults). For example, Sobel et al. (2004) introduced 3- and 4-year-olds to a machine called a “blicket detector” that lit up and played music when certain objects were placed on it (Gopnik & Sobel, 2000). Children were then shown that two novel objects, A and B, together caused the detector to activate when they were placed on the machine. Children were then shown that object A alone activated the machine. Children in both conditions were then asked which of the two objects were blickets and to make the machine go by placing the blicket on the detector. Sobel et al. (2004) found that the 4-year-olds (and to a lesser extent, 3-year-olds) were less likely to place B on the machine than on trials in which object A did not make the machine go by itself (a condition referred to as *indirect screening off*). Using an anticipatory eye-tracking procedure, Sobel and Kirkham (2006) found that 8-month-olds showed this same response pattern.

These findings were interpreted as support for Bayesian inference rather than associative learning. This is because some associative models (e.g., Rescorla-Wagner model) predict that the strength between object B and the machine’s activation is equivalent between the backwards blocking (where A is effective) and indirect screening-off (where A is not effective) trials. However, some caution should be exercised before accepting the conclusion that Bayesian inference rather than associative learning underpins how children process backwards blocking events. One reason is that it is unclear whether the difference in how children treated object B was due to backwards blocking, indirect screening-off, or some combination of both. Both Beckers et al. (2005) and McCormack et al. (2009) were the first to raise this objection. McCormack et al. (2009) showed when a more appropriate operationalization is adopted—in which participants treatment of object B following the standard backwards blocking event (i.e., AB+; A+) is compared to their treatment of object B following a closely matched control event (i.e., AB+; D+)—4-year-olds treated object B equivalently across both trials; the 5-year-olds, in contrast, were more likely to place object B on the machine in the control condition than in the backwards blocking condition. The critical point of agreement between these investigations is that at some point in development, children have the capacity to make retrospective inferences. But the fundamental question remains as to how children engage in such reasoning.

Another reason to exercise caution before accepting the claim that human beings use Bayesian inference to engage in backwards blocking reasoning is that it remains unknown whether human children engage in backwards blocking reasoning for three (or more) objects. Consider a modified version of the standard backwards blocking event in which children first see an ABC+ sequence followed by an A+ sequence. If backwards blocking reasoning is unaffected by the number of presented objects, then children should be less likely to label objects B *and* C as blickets compared to the same objects in a control event in which ABC+ is followed by D+. This question is worth addressing because if the goal is to elucidate and better understand the nature of the cognitive mechanisms that subserve causal reasoning *in the real world*, then it is crucial that we understand how causal reasoning unfolds in situations that mirror children’s natural environments.

One may question whether asking children to reason about three to four objects can really tell us more about the cognitive mechanisms that underpin causal reasoning than asking children to reason about two objects. This is because the two situations differ trivially by at most two potential causes. However, if Bayesian inference is the cognitive mechanism that underpins backwards blocking reasoning in human beings, then the difference between these two settings is far from trivial. This is because in the two-cause setting, participants need only to determine which of *four* candidate causal hypotheses generated the observed data—if each object can either be a blicket or not and children are asked to reason about four blickets, then there are 24 possible combinations of blickets and non-blickets. In contrast, in a three- or four-cause setting like that just discussed, participants need to determine which of *eight* (in the case of 3 objects) or *sixteen* (in the case of 4 objects) hypotheses is the right none. This means that participants must consider up to four times as many causal hypotheses across these two situations.

In light of these unresolved issues, the present investigation had two goals. The first goal was to examine backwards blocking in the presence of multiple potential causes and using a logic like that of McCormack et al. (2009). Five- and 6-year-old children were introduced to a computer-animated “blicket detector” machine and were told that their task was to determine which objects activated the machine. We chose to test 5- and 6-year-olds as opposed to 4-year-olds because the latter group likely has more robust information-processing capacities than the former group and thus a greater chance of engaging in Bayesian inference. Research by Sobel et al. (2017; see also Erb & Sobel, 2014) is consistent with this contention. Participants then received either two backwards blocking and two backwards blocking control trials or two indirect screening-off and two indirect screening-off control trials. Participants in both conditions were then asked to indicate whether the objects in each trial were blickets. The second goal was to determine whether children’s causal inferences were best explained by an associative-learning mechanism or a simple Bayesian mechanism. We did this by fitting a connectionist (associative learning) model and a Bayesian model to participants’ data. The Experiment below addresses the first goal. The “Computational Models” section addresses the second goal.

**Experiment 1**

**Method**

**Participants.** Participants were 32 5-year-olds (16 boys and 16 girls; *M* = 64.81 months, range = 60-71 months) and 31 6-year-olds (17 boys and 15 girls; *M* = 77.81 months, range = 72-83 months). Sample size was determined based on previous studies on backwards blocking reasoning in human children (e.g., Gopnik & Sobel, 2000; 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). Although most children were from white, middle-class backgrounds, a range of ethnicities that resembled the diversity in the population were represented. All children were tested in a quiet room at a local children’s museum.

**Materials.** The “device” used in the current study was a computer-animated version of the canonical blicket detector (e.g., Gopnik & Sobel, 2000). The device was a white rectangle with a black border that measured 5.99 cm × 23.47 cm. If the device was “on”, the white region of the rectangle turned blue. If the device was “off”, the white region remained white. A maximum of 4 differently colored circles were used, and each circle measured 2.67 cm × 2.67 cm (see Figure 2 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 (for the backwards blocking or indirect screening-off trials) or four (for the backwards blocking or indirect screening-off control trials) equally spaced circles appeared above the machine. Finally, the videos contained a built-in script, which experimenters read. All video events were created in Microsoft PowerPoint.

**Procedure.** Participants were tested in a quiet room in local children’s science 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 main portion of the experiment. The pretraining phase began with the triangle (object A) and pentagon (object B) above the machine and next to one another. Object A then descended until it contacted and immediately activated the machine (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 was and was included to ensure that participants understood the task.

Diagram

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Figure 5. 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.

Following the pretraining phase, participants were given four test trials—either the two backwards blocking experimental trials and 2 backwards blocking control trials or two indirect screening-off experimental trials and 2 indirect screening-off control trials—in counterbalanced order using a Latin square. Differently colored objects were used across all trials to prevent carryover effects.

The two backwards blocking main 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 (i.e., 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. The first and second backwards blocking experimental trials were identical except for the object colors (see Figure 5 for a schematic of the backwards blocking experimental event).

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. The experimental and control trials used the same text.

Finally, the indirect screening-off experimental and control conditions were identical to the backwards blocking experimental and control conditions except that objects A (during the indirect screening-off main trials) and D (during the indirect screening-off control trials) failed to activate the machine (see Table 1 for a schematic).

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| --- | --- | --- | --- |
| Schematic of Experiment 1 | | | |
|  | Compound | Elemental | Test |
| backwards blocking experimental trial | ABC+ | A+ | Is A/B/C a blicket? |
| backwards blocking control trial | ABC+ | D+ | Is A/B/C/D a blicket? |
| indirect screening-off experimental trial | ABC+ | A- | Is A/B/C a blicket? |
| indirect screening-off control trial | ABC+ | D- | Is A/B/C/D a blicket? |

Table 1. The +/- signs corresponds to whether the machine activates (+) or not (-)

**Results**

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Figure 6. Participants’ mean responses to whether each object was a blicket across the conditions and trial types. Bars show standard error.

Figure 6 shows the results for this experiment. The dependent measure was the number of times that participants responded “Yes” to the “Is this a blicket” question. Thus, across two trials, the maximum number of times that a participant could respond “Yes” was 2; the minimum number of times that a participant could respond “Yes” was 0. Using this dependent measure, the data were entered into a five-way linear mixed-effects model with Age as a continuous fixed effect, Condition (backwards blocking vs. indirect screening-off) as the between-subjects fixed effect, Trial Type (experimental vs. control),Objects (A vs. B vs. C vs. D), and Phase Order (Phase 1 vs. Phase 2) as the within-subjects fixed effects, and subjects as the random effect. This analysis yielded several main-effects and two-way interactions, which were qualified by 3 three-way interactions. These included a three-way interaction between Age, Condition, and Object, *χ2*(3) = 12.75, *p* = .005, a three-way interaction between Condition, Phase Order, and Object, *χ2*(3) = 13.91, *p* = .003, and a three-way interaction between Condition, Trial Type, and Object, *χ2*(2) = 78.59, *p <* .0001. Given that the lattermost interaction was the only theoretically relevant and meaningful one, all subsequent analyses focused on this interaction. This three-way interaction is shown in Figure 3.

We followed up this three-way interaction with separate one-way linear mixed-effects models for the main and control trials within the backwards blocking and indirect screening-off conditions. The Objects factor was treated as the sole within-subjects fixed effect in these follow-up analyses. Subjects were once again treated as a random effect. The first one-way linear model for the control trials within the backwards blocking condition did not reveal a significant effect of Objects, *χ2*(3) = 1.08, *p* = .78. This means that participants treated the objects similarly during the control trials of the backwards blocking condition. In contrast, the second one-way linear model for the main trials within the backwards blocking condition revealed a significant main effect of Objects, *χ2*(2) = 29.78, *p* < .0001. This main effect reflected the fact that participants considered object A to be more of a blicket (*M* = 1.97, *SD* = 0.18) than object B (*M* = 1.21, *SD* = 0.83), *t*(27) = 4.70, *p<* .001, or object C (*M* = 1.32, *SD* = 0.82), *t*(27) = 4.12, *p* < .001. Participants treated objects B and C equivalently, *t*(27) = -0.72, *p* = .48.

The third and fourth one-way linear models for the main and control trials within the indirect screening-off condition both revealed a significant main effect of Objects, both *χ2*’s > 60.30, both *p*’s < .0001. This reflected the fact that participants considered object A (*M* = 0.52, *SD* = 0.87) to be significantly less of a blicket than objects B (*M* = 1.70, *SD* = 0.67) and C (*M* = 1.74, *SD* = 0.59) during the main condition, both *t*’s > -5.97 and both *p*’s < .0001. Likewise, participants considered object D (*M* = 0.73, *SD* = 0.72) to be less of a blicket than objects A (*M* = 1.76, *SD* = 0.58), B (*M* = 1.69, *SD* = 0.59), and C (*M* = 1.76, *SD* = 0.50) during the control trials, all *t*’s > -6.01, all *p*’s < .001.

To examine whether there was evidence specifically of backwards blocking, data were entered into a two-way linear mixed-effects model with Trial Type and Objects as the within-subjects fixed effects and subjects as the random effect. This analysis revealed only a main effect of Trial Type, *χ2*(1) = 10.14, *p* < .005. This result reflected the fact that participants were more likely to respond that a redundant object was a blicket during the control trials (*M* = 1.60, *SD* = 0.71) than during the main trials (*M* = 1.27, *SD* = 0.82), *F*(1, 139) = 5.28, *p* = .02. This analysis indicates that participants did engage in backwards blocking reasoning.

**Discussion**

The results of Experiment 1 indicated that participants engaged in backwards blocking reasoning. Specifically, participants were more likely to treat the redundant objects as blickets during the backwards blocking control trials than during the backwards blocking experimental trials. These results indicate that participants show some evidence of backwards blocking reasoning when asked to make inferences about multiple candidate causes. However, an open question concerns whether participants will continue to engage in backwards blocking reasoning when two rather than one object participants on the machine during the second (i.e., the A+) phase of the backwards blocking condition.

**Experiment 2**

**Method**

**Participants.** ADD RELEVANT INFO WHEN WE GET IT.

**Stimuli, Design, and Procedure.**  All aspects of Experiment 2 were identical to Experiment 1 with one exception: Two objects participated on the machine during the elemental phases of the backwards blocking and indirect screening-off events. Thus, participants in the backwards blocking condition saw an ABC+ AB+ series of events during the experimental trials and an ABC+ DE+ series of events during the control trials. In contrast, participants in the indirect screening-off condition saw an ABC+ AB- series of events during the experimental trials and an ABC+ DE- series of events during the control trials. Similar to Experiment 1, to prevent potential carryover effects differently colored objects were used across all trials to prevent carryover effects and the left-right positions of objects A and B during the experimental trials and D and E during the control trials in both conditions were counterbalanced.

Computational Models

**A simple Bayesian computational model**

A key assumption of Bayesian inference is that causal induction is a process that involves representing the entire space of candidate causal hypotheses—which can be expressed as parameterized causal graphical models with nodes that are connected by edges that encode the Markov condition—and then choosing the hypothesis that is most consistent with the data. We can use Bayes rule to choose among these hypotheses. Formally, it is assumed that at the beginning of a learning episode, an ideal learner represents all possible candidate hypotheses, *H*, whereby each hypothesis, *h* ∈ *H*, is assigned some prior probability, *p*(*h*). This prior probability represents the learners’ confidence that a given hypothesis generated that causal data. Figure 7 below shows the hypothetical hypothesis space for three objects.

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**Timeline

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Figure 7. 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.

Following observations of data, *d*, the learner uses Bayes' rule to compute and assign posterior probabilities to each hypothesis, *p*(*h*|*d*),

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where *p*(*d*|*h*) represents the likelihood or the probability of the data *d* under a given hypothesis *h*. The denominator serves as the normalizing term—it allows the posterior probabilities the hypotheses to sum to 1. Given that the machine behaved deterministically in the present context (i.e., objects either produce or do not produce detector activation), the likelihoods are set to 1 whenever a link (i.e., causal relation) exists in the hypothesis and is consistent with the observed data; otherwise, they are set to 0. Once we have determined whether such a link exists for a particular object, we can compute the likelihood that any of the objects is a blicket by taking the product of the likelihood that that object activated the detector under each hypothesis and the prior probability of each hypothesis and then summing this product. For example, to determine the probability that object B is a blicket, we can compute the following equation

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where equals 1 if a causal link between *B* and *E* existsfor a specific hypothesis *h*; otherwise, equals 0.

Crucially, because the predictions of this (or any) Bayesian model will depend on the “prior probability” that any given object is a blicket, below we show the predictions of the model when the probability of a blicket is .5, .65, .8, .95, and 1. Figure 8 shows the model’s predictions for Experiment 1 and Figure 9 shows the model’s predictions for Experiment 2. We also plotted the model’s predictions for various prior probabilities because it was unclear what participants’ baseline assumptions would be 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 (qualitatively and quantitatively) the model’s predictions for the different probabilities to children’s actual treatment of the objects. Figure 8A-E shows these predictions. We also plotted the model’s predictions for various prior probabilities because it was unclear what participants’ baseline assumptions would be 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. Figure 8A-E shows these predictions.

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| Chart, bar chart  Description automatically generated  A | Chart, bar chart  Description automatically generated  B |
| Chart, bar chart  Description automatically generated  C | Chart, bar chart  Description automatically generated  D |
| Chart  Description automatically generated  E |  |

Figure 8. This figure displays the of the Bayesian model for the backwards blocking and indirect screening-off conditions when *P*(Blickets) = .5 (3A), *P*(Blickets) = .65 (3B), *P*(Blickets) = .8 (3C), *P*(Blickets) = .95 (3D), *P*(Blickets) = 1 (3E).

As shown in Figure 8A-E, the model predicts that during the backwards blocking experimental and control trials participants should be maximally confident that objects A and D are blickets. In contrast, during the indirect screening-off experimental and control trials, participants should be maximally confident that objects A and D are not blickets. Importantly, the model makes these predictions regardless of the prior probability of blickets. In contrast, the model predicts that participants should categorize objects B and C at the same rate across the main trials in the backwards blocking and indirect screening-off conditions and objects A-C at the same rate across the corresponding control trials.

**A simple connectionist computational model**

To examine whether participants’ inferences in the present experiment are best explained by an associative-learning mechanism we built a simple two-layer connectionist model. The network architecture is shown below in Figure 9. The model used to simulate the experiment reported here consisted of an input layer and an output layer—there were no hidden layers in these models. The input layer for the model consisted of four units, and the output layer consisted of a single unit. Each input unit corresponded to each of the four possible objects used in the experiment. Whenever an object was present, the activation value of its corresponding input unit was set to a value of “1”; the activation of these units was set to a value of “0” if the corresponding objects were not present. If a predetermined blicket was presented at the input layer, then the model was trained to turn on the single output unit (i.e., to produce an activation of 1). This process corresponded to an object activating the blicket machine. All simulations used a learning rate of .05 but no momentum. Model weights were initialized to 0, and the output units used sum-squared activation functions.

Diagram

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Figure 9. The neural network model used in the simulations reported here.

The models were trained on the same events as children. For example, networks, like children, were assigned randomly to the indirect screening-off condition or to the backwards blocking condition. To match the behavioral experiment, networks experienced two of each kind of event within a given condition. For example, during the two “experimental trials” for networks in the backwards blocking condition, the first three input units were turned on (i.e., the activation of each input node was set to a value of 1), and the network’s task was to learn to activate the single output unit (i.e., to set the activation of the single output unit to 1). Turning on the first three input units simulated placing objects A, B, and C on the blicket machine, and training the model to turn on the single output unit corresponded to networks learning that A-C activated the machine. This segment of training corresponded to the ABC+ events. During the subsequent A+ trials, only the first input unit was turned on, but again the network’s task was to activate the single output unit. The backwards blocking control trials were identical to the backwards blocking experimental trials except that the fourth input unit (corresponding to object D) rather than first input unit was turned on. The indirect screening off experimental and control trials were identical to the backwards blocking experimental and control trials except that the network was trained to turn off the single output unit (i.e., set its value to 0) during the A- and D- phases of the indirect screening-off experimental and control trials, respectively. The compound (e.g., ABC+) and elemental (e.g., A+/D+; A-/D-) phases—which were shown twice to be consistent with the behavioral study—lasted 200 epochs each. This mean that one complete simulation lasted 800 (i.e., 400 × 2) epochs. The predictions that this model makes for how participants should treat the different objects across the trials and conditions are shown below in Figure 8.Although we report the results of a model that was trained for 800 total epochs in the main text, we ran additional simulations to ensure that the main results were not idiosyncratic to the precise number of training epochs.

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A

Figure 84. Connectionist model predictions for how participants should treat the objects between the main and control trials of the backwards blocking and indirect screening-off conditions.

B)

Qualitatively, the model predicts that participants should treat objects A-C equivalently during the backwards blocking experimental trials. In contrast, the model predicts that participants should treat object A as more of a blicket than objects B and C during the same trials. For the indirect screening-off experimental trials, the model predicts that participants should treat object A as less of a blicket than objects B and C during the indirect screening-off experimental trials.

It should be noted that the Bayesian and connectionist model make identical qualitative predictions for all the conditions and trials except for the backwards blocking control condition: the simple connectionist model predicts that participants should treat objects A-D equivalently during this trial; the simple Bayesian model predicts that participants should only treat objects A-C equivalently but should be maximally confident that object D is a blicket. Thus, it should be possible to determine which model participants relied on based on their performance during the backwards blocking control condition. Interestingly, both models predict that participants’ treatment of the redundant causes between the backwards blocking experimental and backwards blocking control trials should not differ. Likewise, both models predict that participants’ treatment of the redundant causes between the backwards blocking main and indirect screening-off main conditions should not differ. Thus, the simple connectionist model and Bayesian model do not predict backwards blocking reasoning according either to the new or old operationalization of backwards blocking reasoning. The present study was designed to test these predictions.

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| **Chart, bar chart  Description automatically generated**  A | |
| Chart, bar chart  Description automatically generated  B | Chart, bar chart  Description automatically generated  C |

Figure 7A-C. Participants data (6A) compared to the predictions of the best-fitting connectionist model trained for 800 epochs (6B) and the best fitting Bayesian model, where the *P*(Blicket) = .80 (6C).

**Qualitative and Quantitative Model fits**

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 and participants’ mean responses to objects A-C during the backwards blocking and indirect screening-off main trials and objects A-D during the backwards blocking and indirect screening-off control trials. These two metrics have been used in previous simulation studies to assess model’s quantitative fit to behavioral data (e.g., Bhat et al., 2022). Lower values on each metric indicate better model fit. Table 2 shows the fits for the different model instantiations.

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| --- | --- | --- |
| Computational Models | root mean square (RMSE) | mean absolute error (MAE) |
| Connectionist Model (800 epochs)++ | .19 | .15 |
| Connectionist Model (1600 epochs) | .22 | .16 |
| Connectionist Model (2000 epochs) | .25 | .17 |
| Connectionist Model (3000 epochs) | .28 | .22 |
| Bayesian model (.5) | .58 | .54 |
| Bayesian model (.65) | .39 | .34 |
| Bayesian model (.80)++ | .29 | .21 |
| Bayesian model (.95) | .39 | .33 |
| Bayesian model (1) | .45 | .39 |

Table 2. Model fit indices for the various models and instantiations. ++ indicates the best fitting connectionist and Bayesian models.

It should be clear from the table above that the connectionist model provided a better quantitative fit to the behavioral data than any of the Bayesian models. It should also be clear that the connectionist model provides a better *qualitative* fit to the data than the Bayesian model. This is most evident when one considers the model’s predictions for participants’ judgements during the backwards blocking control trials and the model’s predictions for these trials. The connectionist model predicted that participants should treat the four objects equivalently, which the behavioral data supported. In contrast, the Bayesian model predicted that participants should treat object A differently than the other objects, which the behavioral data did not support.

Given that the connectionist model instantiated associative learning, these results suggest that participants may have used associative learning rather than Bayesian inference to process the present events. We discuss below the exact nature of this associative learning.

General Discussion

This study had two aims. The first was to determine whether 5- and 6-year-olds would engage in backwards blocking reasoning for 3 and 4 objects. This departs from the typical convention of using two objects to study causal reasoning in human children. The second aim was to clarify how exactly (i.e., the cognitive mechanism by which) children reasoned about the present causal events. We were specifically interested in whether children’s causal inferences best conformed to the predictions of a simple Bayesian model or a connectionist (associative learning) model.

With respect to the first aim, we found evidence of backwards blocking reasoning under the old operationalization of backwards blocking reasoning but only minimal evidence of such reasoning under a new and more valid measure of backwards blocking reasoning. This finding extends previous research to show that when children are asked to reason about three objects and a more valid of operationalization of backwards blocking reasoning is used, children minimally engage in backwards blocking reasoning.

With respect to the second aim, the data were most consistent with the connectionist (associative learning) models. However, a question that we have not yet answered concerns the exact nature of the connectionist models’ associative learning. Specifically, how did these models—via associative learning—arrive at their causal judgements? To understand how the connectionist model’s judgements arose mechanistically, consider the backwards blocking (i.e., ABC+ D+) control trial. The rationale for focusing on this condition is that the connectionist uniquely predicts participants performance during the backwards blocking control condition. 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 single output unit was equivalent for all four objects, the network made the same weight adjustments both in sign and magnitude to the connections (which encode associations) between each object and the single output unit. This explains why the network responded equivalently when “asked” whether each object (i.e., objects A-D) was a blicket. Given that participants’ causal responses mirrored the predictions of the connectionist model, this suggest that children arrived at their causal judgements via a similar associative-learning process. This finding is significant because it has been suggested that causal reasoning in human children is best explained by Bayesian inference and rational processes rather than by associative processes. The present data add nuance and context to this debate by suggesting that whether children engage in Bayesian inference or associative learning may depend on how causal reasoning is measured and the number of objects about which they are asked to reason.

These aims aside, some potential criticisms are worth noting. One such potential criticism is that the results are inconsistent with the findings from previous studies on backwards blocking reasoning in human children. Such previous research showed that children unequivocally engage in backwards blocking reasoning when asked to reason about two objects; in contrast, the current study only provided equivocal evidence for backwards blocking reasoning when three and four objects were used. However, we believe that the present results extend rather than are at odds with such previous research. Specifically, the present study likely demonstrates that when children’s information-processing capacities are stretched such as when they are asked to reason about multiple potential causes, they may deploy and rely on simpler associative processes. Although the numerical difference between three and four objects is miniscule, by contrast the corresponding increase in the size of the underlying psychological hypothesis space is substantial. Such an increase in the size of the underlying psychological hypothesis space may have important ramifications on the cognitive mechanism that gets deployed by children, especially if children are sensitive to and affected by this increase. For example, children who are asked to reason about two candidate causes need only to represent and choose among *four* candidate causal hypotheses. Four candidate causal hypotheses may well be within the information-processing capacities of 5- and 6-year-olds. In contrast, children who are asked to reason about three candidate causes must now consider *eight* candidate causal hypotheses—this may exceed their restricted information-processing capacities.

It turns out that there is a wealth of data that is consistent with this general proposal (Doebel & Zelazo, 2015; Frye, Zelazo, & Palfai, 1995; Zelazo, Frye, & Rapus, 1996; Zelazo et al., 2003). One recent study by Kenderla and Kibbe (2023) showed that when 8- and 10-year-old children’s information-processing abilities were stretched in a virtual memory game—such as when children were asked to find three cards that shared one feature and differed on another feature—they relied less on working memory and more on manual exploration. Given that children were not required actively to maintain information in memory when manually exploring, manual exploration was an ostensibly simpler and less cognitively effortful strategy than one that required working memory. In a similar vein, Richland, Morrison, and Holyoak (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. Finally, there is evidence that preschool-age children's 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).

Together, this research demonstrates that although children can process information at higher levels, if the task that they are given requires information-processing abilities that extend beyond what they possess, then there will be a tendency for them to process information at lower levels and to rely on less sophisticated strategies and cognitive mechanisms. This may provide a developmental explanation for why children in the present study did not engage in backwards blocking reasoning or show evidence that they relied on Bayesian inference. A testable prediction of this account is that there should be a point at which children go from using a simple associative-based counting mechanisms in contexts like the present one to more rationale processes like Bayesian inference. This issue should be explored more fully in future research.

A second potential criticism is that we cannot be sure that a simple Bayesian-inference mechanism underpinned participants’ performance in the present study. For example, if participants assumed that blickets were common in the present context—which is plausible given how frequently the detector activated in the present study—then participants should be *less* likely to block redundant causes; in other words, participants should be *more* likely to treat all potential blickets (expect for the ones that are explicitly shown not to be causal) equally. This could explain participants’ performance in the backwards blocking control condition—in that condition, participants treated all objects equally. However, this explanation cannot explain *all* the present data. This is because this explanation predicts that participants should have also treated objects A-C equivalently in the backwards blocking experimental condition as well, but this was not the case: Participants treated object A differently than either objects B or C in the backwards blocking experimental condition. This explanation is also unlikely given that, over all the Bayesian models provided a poorer fit to the behavioral data than the connectionist models. This would not be expected if participants relied on Bayesian inference. Nonetheless, because we did not systematically manipulate base-rate information, this alternative explanation cannot be ruled out entirely. However, if we are correct that participants do not rely on Bayesian inference when asked to reason about multiple causes, we predict that their performance in this proposed future study would not differ from participants’ performance in the current study. However, if children’s causal judgements are affected by base-rate information, such that, overall, how they process backwards blocking event changes with changes to base-rate information, then this would suggest that participants may use Bayesian inference after all to reason about multiple candidate cause, at least when a Bayesian-inference mechanism is primed by explicitly and systematically manipulating base-rate information.

**Conclusion**

These potential criticisms notwithstanding, this study constitute one of the first systematic attempts to examine backwards blocking and indirect screening-off reasoning in human children in the context of three and four objects. A longstanding view has been that the cognitive mechanism by which human beings reason about causal events is Bayesian inference (e.g., Gopnik et al., 2004) rather than associative processes. The experiments reported here support a different conclusion: associative learning is sufficient to explain 5- to 6-year-old children’s reasoning about multiple potential causes.

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