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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Data availability statement: The code and network-modeling scripts are available upon reasonable request.

Conflicts of interests: none

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 (BB) and indirect screening-off (IS) 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 BB 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

There is perhaps no ability that is more central for learning about how the world works than causal reasoning or the capacity to make inferences about cause-and-effect relations. This is a key cognitive ability because it enables human learners to encode causal relations to inform prediction and inference (e.g., Oakes & Cohen, 1990; Rakison, Smith, & Ali, 2016; Schlottmann & Shanks, 1992), to intervene on those relations to generate new effects (e.g., Gopnik et al., 2001), and counterfactually to reason about causal events to determine what would have happened if alternative actions were chosen (e.g., Harris, German, & Mills, 1996; Sobel, 2004).

The ability to reason about causal events is thought generally to emerge between 18 months and 5 years of age (e.g., Benton, Rakison, & Sobel, 2021; Gopnik & Sobel, 2000; Gopnik et al., 2001; Kimura & Gopnik, 2019; Meltzoff, Waismeyer, & Gopnik, 2012; Sobel & Kirkham, 2006, 2007; Sobel & Munro, 2006; Walker & Gopnik, 2014; cf. Sobel & Kirkham, 2005). To date, most studies on causal reasoning in human children have used the blicket-detector design. In these studies, children are introduced to a machine called the "blicket detector" and told that it lights up and plays music when certain objects—namely, "blickets"—are placed on it but not when non-blickets are placed on it. Children are then asked to determine which objects are blickets and to “make the machine go” by placing the blicket on the machine.

There have been several important findings to come from research with the blicket detector, but the finding that has generated that the most controversy was that by Sobel, Tenenbaum, and Gopnik (2004). They showed that by 4 years of age children can engage in two forms of causal reasoning called “backwards-blocking” (henceforth, BB) reasoning and “indirect screening-off” (henceforth, ISO) reasoning. BB reasoning is the process by which learners discount or “block” causal cues that are revealed to be redundant in producing some effect. ISO reasoning is the process by which learners discount or “screen off” a causal cue whose causal status is known unambiguously.

In their study, children were first shown that two novel objects, objects A and B, together caused the detector to activate when both objects were placed on the machine. Children were then shown that object A alone either failed to activate the detector (i.e., AB+ A-; ISO condition) or activated the detector when placed on it (i.e., AB+, A+; BB condition). 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 responded by placing object B on the machine in the ISO condition; these same children responded by placing object A on the machine in the BB condition. Subsequent research by Sobel and Munro (2009) found that 3-year-olds could also engage in BB and ISO reasoning if the machine was given the properties and desires of animate entities.

These findings were interpreted to mean that human children can engage in BB reasoning and that this form of reasoning is underpinned by a Bayesian-inference mechanism. The crux of the Bayesian-inference account is that human learners use a simple form of Bayes’ rule to reason about causal events and to choose the causal hypothesis—within a space of hypotheses that is potentially super-exponentially large—that is most consistent with the observed data (e.g., Sobel et al., 2004; Gopnik & Wellman, 2012). Crucially, proponents of this perspective have argued that associative learning cannot underlie human causal reasoning. The associative-learning model that has received perhaps the most criticism is the traditional Rescorla-Wagner (henceforth, RW) model (e.g., Rescorla & Wagner, 1972; Griffiths et al., 2011; Sobel et al., 2004). One reason that this model has been called into question is that it predicts that object B should be treated equivalently across the BB and ISO conditions—this prediction is at variance with participants’ actual treatment of object B across these conditions. We return to the issue of what cognitive mechanism underlies causal reasoning in human children in a few paragraphs.

However, some caution should be exercised either before accepting the conclusion that human children can engage in BB reasoning, to say nothing of the cognitive mechanism that underpins this form of reasoning. One major reason to exercise caution concerns the fact that there are problems with how BB reasoning has been operationalized in previous research. For example, Sobel et al. (2004; see also Beckers et al., 2009; McCormack et al. 2009, Exp. 1; Sobel & Kirkham, 2006) operationally defined BB reasoning as greater B choices in the ISO condition than in the BB condition (although for alternative operationalizations, see De Houwer, Beckers, & Glautier, 2002; Larkin, Aitken, & Dickinson, 1998; Griffiths et al., 2011; Kruschke & Blair, 2000; Lovibond et al., 2003; Shanks, 1985; Van Hamme and Wasserman, 1994). This way of operationally defining BB reasoning was likely motivated by two key factors. First, if the causal status of object A—which can be determined unequivocally when object A is placed alone on the machine—causes participants retrospectively to reevaluate the causal status of object B, then participants *should* consider B to be less of a blicket in the BB condition than in the ISO condition.

There are two key limitations with this operationalization, however. First, as Beckers et al. (2005) and McCormack, Butterfill, Hoerl, and Burns (2009) pointed out, it cannot be determined why participants treated object B differently between the BB and ISO condition. Differential treatment of object B could have been due to a BB effect, an ISO effect, or both. Such differential treatment could have also resulted from the fact that participants observed a positive effect during the elemental (i.e., A+) phase in the BB condition but a negative effect during the elemental (i.e., A-) phase in the ISO condition. Crucially, this would not be a true retrospective reevaluation of object B by participants based on A’s *relation to and effect* *on* object B across both conditions (which is the intended inference).

The operationalization that we adopt here—which was first introduced by McCormack et al. (2009, Exp. 2)—eschews this limitation. On this operationalization, BB reasoning is assessed by comparing how participants treat object B following an AB+ A+ sequence of events (i.e., the BB experimental condition) to how participants treat object B following an AB+ C+ sequences of events (i.e., the BB control condition). These two conditions differ in terms of the object that is shown during the elemental phase (i.e., A or C) and that object’s *relation* to B (and thereby the potential impact that this object has on how B is treated). For example, in the BB experimental condition, a dependency is presumably established between objects A and B because both objects appear together during the compound phase of the condition. This means that the observed causal efficacy of object A during the subsequent elemental phase *should* affect participants’ (retrospective) treatment of object B. In contrast, in the BB control condition, object C never appeared with object B, which necessarily means that C’s causal status should not affect how participants evaluate object B. Crucially, the blicket effect itself is held constant across the BB experimental and control conditions. In other words, across both conditions the machine activates in compound and elemental phases. If participants do engage in BB reasoning in this new context with an appropriate control, and BB reasoning is treated as an indirect measure of the operation of a Bayesian-inference mechanism as has typically been the case (e.g., Griffiths et al., 2011; Sobel & Kirkham, 2006; Sobel et al., 2004), then this would provide stronger evidence that such a mechanism is available to human children.

**An open question**

It turns out that there is still another reason to exercise caution before accepting the claim that human beings engage in BB reasoning and rely on a Bayesian-inference mechanism to do it. This has to do with the fact that it is not known whether human children engage in BB reasoning for three (or more) objects. The is because most, if not all, of the studies on BB reasoning in human children have tended to use two objects; that is, participants are shown an AB+ A+ sequence of events and then asked whether each object is a blicket. This research is important because it has revealed that BB reasoning may emerge by 3 years of age, but it leaves unaddressed whether children can engage in BB reasoning when asked to reason about three or more objects. This issue is worth addressing because if a Bayesian-inference mechanism is assumed to underpin human causal reasoning as measured by participants’ BB performance, then it is crucial to show that participants continue to engage in BB reasoning (and thus make use of Bayesian inference) even when they are asked to reason about three (or more) objects. In other words, if one of the goals of research on causal reasoning in human children is to elucidate the cognitive mechanisms by which children reason causally *in the real world*, then it is crucial that we understand how causal reasoning unfolds in situations that more closely approximate those that may be found the real world such as those with multiple objects.

One may question whether a setting in which children are asked to reason about three and four objects really would tell us more about the nature of the cognitive mechanism that supports causal learning and BB reasoning than the typical setting in which children are asked to reason about two objects. This is because these two settings differ by at most two candidate causes, which is a difference that may seem trivial. However, if Bayesian inference is the cognitive mechanism that underpins human causal reasoning and BB inference, then the difference between these two settings is far from trivial. This is because in the two-candidate-cause setting, participants need only to determine which of *four* candidate causal hypotheses generated the observed data. However, in the three- or even four-candidate-cause setting, participants need to determine which of *eight* (in the case of 3 candidate causes) or *sixteen* (in the case of 4 candidate causes) hypotheses is the one that generated the observed data. Thus, in the four-candidate-cause setting, participants must consider four times as many causal hypotheses as participants in the two-candidate-cause setting. This is not a trivial difference.

Crucially, this difference may have important implications for whether an associative-learning mechanism or a Bayesian-inference mechanism underlies causal reasoning in children. For instance, it is possible that when children’s information-processing abilities are taxed—such as when they are asked to reason about three (or more) objects (see the General Discussion for a fuller discussion)—they may resort to simpler modes of causal reasoning such as reasoning that is consistent with the predictions of the traditional RW model or some other associative-learning process.

Thus, if participants’ BB performance adheres to the predictions of the traditional RW model or to the predictions of even simpler models of associative learning (see below) in a multiple-candidate-cause setting, this would suggest that the conclusion that the traditional RW model or other associative processes are ill-equipped to explain causal reasoning in human children may have been made prematurely. Thus, by understanding whether participants engage in BB reasoning in a multiple-candidate-cause setting, we can gain greater insight into *how* children reason about causal events and under what conditions they use one kind of cognitive mechanism in lieu of another.

**Possible cognitive mechanisms underlying BB reasoning for multiple potential causes**

Given that the goal of the present paper is to determine what underlying cognitive mechanism best accounts for participants' performance in the present paper, it was important to determine what predictions a Bayesian-inference mechanism, the traditional RW model, and a simple associative-learning counting mechanism makes for how participants should perform in the present context. Note that here we only describe these cognitive mechanisms and outline their predictions at a high level. However, we direct the reader to the Appendix for the formal details of the Bayesian model and the details of the traditional RW model.

**Bayesian inference.** Proponents of the Bayesian-inference account maintain that human learners use a simple form of Bayes’ rule to reason about causal events. Specifically, this perspective maintains that a learners’ responsibility is to determine which hypothesis—within a space that contains potentially an infinite number of psychological hypotheses—is the one that is generatings some observed data. The proposed cognitive mechanism by which learners determine such a “winning” hypothesis is by combining their prior beliefs about each hypothesis (in the absence of data; this is sometimes called the “prior”) with whether the observed data is likely to have been produced by the hypothesis that is currently under consideration (this is sometimes called the “likelihood”). Crucially, learners will retain a hypothesis to the extent that it can produce the observed data. Learners will discard a hypothesis when it no longer can produce the data. A core assumption of Bayesian inference is that the probability of a given hypothesis (given some data; i.e., the “posterior probability” of a given hypothesis) at one point in time becomes the prior probability of that hypothesis at the next point in time, and the process that was just described for how one isolates the winning hypothesis repeats when new data is encountered. Crucially, once the posterior probabilities have been computed, learners may use them to update their beliefs about the likelihood that particular objects, rather than particular hypotheses, are blickets.

Thus, given that learners are asked to reason about a maximum of three candidate causes (i.e., objects A-C) during the experimental trials in the both the BB and ISO conditions and a maximum of four candidate causes during the control trials in both the BB and ISO conditions (i.e., objects A-D), the corresponding psychological hypothesis spaces consist, respectively, of 8 and 16 hypotheses (Figs. 1 & 2).

**Timeline

Description automatically generated with medium confidence**

Figure 1. 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.

By application of Bayes’ rule, the prediction that this model makes for how participants should treat the objects after the BB main trial is shown below in Table 1.

|  |  |  |
| --- | --- | --- |
| **Bayesian Model Predictions (3 objects) – BB main** | | |
| **Graphs** | **Prior (*p*(*h*))** | **After AB+ A+ (*p*(*h|d*))** |
| Model 0 | *p*3 | *p*2 |
| Model 1 | *p*2(1-*p)* | *p*(1-*p*) |
| Model 2 | *p*2(1-*p)* | *p*(1-*p*) |
| Model 3 | *p*(1-*p*)2 | (1-*p*)2 |
| Model 4 | *p*2(1-*p*) | 0 |
| Model 5 | *p*(1-*p*)2 | 0 |
| Model 6 | *p*(1-*p*)2 | 0 |
| Model 7 | (1-*p*)3 | 0 |
| Probabilities of objects A, B, and C | | |
| Object A | *p* | 1 |
| Object B | *p* | p |
| Object C | *p* | *p* |

As can be seen, this model predicts that for any probability *p,* following the AB+ A+ BB experimental or main event participants should be maximally confident that object A is a blicket but should treat objects B and C equivalently; that is, they should produce an equivalent number of “yes” responses when asked whether objects B and C are blickets. The predictions that this model makes after the ISO main trial are shown below in Table 2.

|  |  |  |
| --- | --- | --- |
| **Bayesian Model Predictions (3 objects) – ISO main** | | |
| **Graphs** | **Prior (*p*(*h*))** | **After AB+ A- (*p*(*h|d*))** |
| Model 0 | *p*3 | 0 |
| Model 1 | *p*2(1-*p)* | 0 |
| Model 2 | *p*2(1-*p)* | 0 |
| Model 3 | *p*(1-*p*)2 | 0 |
| Model 4 | *p*2(1-*p*) | *p*2 |
| Model 5 | *p*(1-*p*)2 | *p*(1-*p*) |
| Model 6 | *p*(1-*p*)2 | *p*(1-*p*) |
| Model 7 | (1-*p*)3 | (1-*p*)2 |
| Probabilities of objects A, B, and C | | |
| Object A | *p* | 0 |
| Object B | *p* | *p* |
| Object C | *p* | *p* |

As is shown in Table 2, this model predicts that for any probability *p*, following the ABC+ A- ISO main trials participants should be maximally confident that object A is *not* a blicket but should treat objects B and C equivalently. In terms of the control trials for the BB and ISO condition, the hypothesis space—which consists of 16 hypotheses—is shown below.

Timeline

Description automatically generated

Figure 2. The sixteen different causal hypotheses indicating the possible causal relations for a causal event that involves three objects and one blicket detector. *A*, *B*, *C*, and D correspond to the four objects that were used on the machine and *E* indicates the activation of the machine.

The predictions that this model makes for the BB control trials—that is, for the ABC+ D+ trials—are shown below in Table 3.

|  |  |  |
| --- | --- | --- |
| **Bayesian Model Predictions (4 objects) – BB control** | | |
| **Graphs** | **Prior (*p*(*h*))** | **After ABC+ D+ (*p*(*h|d*))** |
| Model 0 | *p*4 | *p*3 |
| Model 1 | *p*3(1-*p*) | 0 |
| Model 2 | *p*3(1-*p*) | *p*2(1-*p*) |
| Model 3 | *p*2(1-*p*)2 | 0 |
| Model 4 | *p*3(1-*p*) | *p*2(1-*p*) |
| Model 5 | *p*2(1-*p*)2 | 0 |
| Model 6 | *p*2(1-*p*)2 | *p*(1-*p*)2 |
| Model 7 | *p*(1-*p*)3 | 0 |
| Model 8 | *p*3(1-*p*) | *p*2(1-*p*) |
| Model 9 | *p*2(1-*p*)2 | 0 |
| Model 10 | *p*2(1-*p*)2 | *p*(1-*p*)2 |
| Model 11 | *p*(1-*p*)3 | 0 |
| Model 12 | *p*2(1-*p*)2 | *p*(1-*p*)2 |
| Model 13 | *p*(1-*p*)3 | 0 |
| Model 14 | *p*(1-*p*)3 | (1-*p*)3 |
| Model 15 | (1-*p*)4 | 0 |
| Probabilities of objects A, B, C, and D | | |
| Object A | *p* | *p* |
| Object B | *p* | *p* |
| Object C | *p* | *p* |
| Object D | *p* | 1 |

As is evident, the model predicts that for any probability *p*, following the ABC+ D+ BB control trials participants should be maximally confident that object D is a blicket after the BB control trials but should treat objects A-C equivalently. Finally, the predictions that the model makes for the ISO control trials—that is, for the ABC+ D- trials—are shown below in Table 4.

|  |  |  |
| --- | --- | --- |
| **Bayesian Model Predictions (4 objects) – ISO control** | | |
| **Graphs** | **Prior (*p*(*h*))** | **After ABC+ D- (*p*(*h|d*))** |
| Model 0 | *p*4 | 0 |
| Model 1 | *p*3(1-*p*) | *p*3 |
| Model 2 | *p*3(1-*p*) | 0 |
| Model 3 | *p*2(1-*p*)2 | *p*2(1-*p*) |
| Model 4 | *p*3(1-*p*) | 0 |
| Model 5 | *p*2(1-*p*)2 | *p*2(1-*p*) |
| Model 6 | *p*2(1-*p*)2 | 0 |
| Model 7 | *p*(1-*p*)3 | *p*(1-*p*)2 |
| Model 8 | *p*3(1-*p*) | 0 |
| Model 9 | *p*2(1-*p*)2 | *p*2(1-*p*) |
| Model 10 | *p*2(1-*p*)2 | 0 |
| Model 11 | *p*(1-*p*)3 | *p*(1-*p*)2 |
| Model 12 | *p*2(1-*p*)2 | 0 |
| Model 13 | *p*(1-*p*)3 | *p*(1-*p*)2 |
| Model 14 | *p*(1-*p*)3 | 0 |
| Model 15 | (1-*p*)4 | (1-*p*)3 |
| Probabilities of objects A, B, C, and D | | |
| Object A | *p* | *p* |
| Object B | *p* | *p* |
| Object C | *p* | *p* |
| Object D | *p* | 0 |

As shown in Table 4, the model predicts that for any probability *p*, following the ABC+ D- ISO control trials participants should be maximally confident that object D is *not* a blicket but should treat objects A-C equivalently. Taken together, a simple Bayesian model predicts that learners should be maximally confident about the status of a candidate cause when it is shown in isolation but should treat objects that are shown in combination (and never alone) equivalently.

**Associative learning: the traditional RW model.** In contrast to a simple Bayesian model, learners who rely on a cognitive mechanism that can be captured by the traditional RW model should adjust their beliefs about the status of a candidate cause by an amount that is equal to the difference between the outcome that participants observe and participants’ beliefs about whether a given candidate cause will activate the machine. On this account, this difference is “scaled” by the salience of the effect (i.e., how causal the effect appears) and the salience of the candidate causes. Crucially, unlike the simple Bayesian-inference model above, learners who use this mechanism to reason about causal events need not represent a psychological hypothesis space. Rather, learners’ inferences are based on prediction error between what they observe and what they expect. The predictions that this model makes for how participants should treat the objects after the BB main and control trials and after the ISO main and control trials are shown below in Table 5.

|  |  |  |
| --- | --- | --- |
| **The traditional RW model (3 objects) – BB main** | | |
| A | *p* | 1 |
| B | *p* | *p* |
| C | *p* | *p* |
| **The traditional RW model (3 objects) – ISO main** | | |
| A | *p* | 0 |
| B | *p* | *p* |
| C | *p* | *p* |
| **The traditional RW model (4 objects) – BB control** | | |
| A | *p* | *p* |
| B | *p* | *p* |
| C | *p* | *p* |
| D | *p* | 1 |
| **The traditional RW model (4 objects) – ISO control** | | |
| A | *p* | *p* |
| B | *p* | *p* |
| C | *p* | *p* |
| D | *p* | 0 |

As can be seen in Table 5, this model, like the simple Bayesian model, predicts that learners should be maximally confident about the status of a candidate cause when it is shown in isolation, but should treat objects that are shown in combination (and never alone) equivalently. Thus, if participants’ performance aligns with the predictions of these two models, it should be impossible to determine whether a Bayesian mechanism or an associative-learning mechanism—based on the mechanics of the traditional RW model—underlies children’s performance in this task, and an additional experiment will need to be conducted.

**Associative learning: a simple “counting” cognitive mechanism.** A third potential cognitive mechanism that children may rely on to reason about the present causal events is based on a simple associative “counting” strategy based on the frequency with which (i.e., the number of times that) a given object—either individually or in combination with other objects—appeared with the blicket effect. To understand how this cognitive mechanism works to produce causal judgements, consider the ABC+ D+ BB control trial. If counting is the cognitive mechanism that best explains learners’ inferences in the present task, then following the BB control event learners should treat objects A-D equivalently. This is because all four objects would have been paired with the machine’s activation an equal number of times. In other words, object A would have been seen with the machine’s activation exactly once, object B would have been seen with the machine’s activation exactly once, object C would have been seen with the machine’s activation exactly once, and object D would have been seen with the machine’s activation exactly once. As such, the strength of the associative relation (or link) between each object and the effect should be equivalently for all four objects. It should be noted that although children observed trials during which objects were placed on the machine in triplets, learners who rely on a counting mechanism are nonetheless considering each object separately and are counting the frequency with which a given object is paired with the machine’s activation.

It should be clear that although a counting-based mechanism and the traditional RW model are associative-learning processes and thus are related, they differ crucially in their predictions. For instance, learners who rely on the traditional RW model to make causal inferences should adjust their beliefs about the causal status of an object based on prediction error. In contrast, if a simple counting-based mechanism underlies learners’ causal inferences in the present context, then they should increase their belief that a given object is causally effective based on the number of times that that object and the machine’s activation have been paired. Below in Table 6 are the predictions that this account makes for all four conditions.

|  |  |  |  |
| --- | --- | --- | --- |
| The predictions of a simple associative-based counting mechanism | | | |
| BB main – ABC+ A+ | | | |
| Is A a blicket? | Is B a blicket? | Is C a blicket? | Is D a blicket? |
| +2 | +1 | +1 | N/A |
| BB control – ABC+ D+ | | | |
| Is A a blicket? | Is B a blicket? | Is C a blicket? | Is D a blicket? |
| +1 | +1 | +1 | +1 |
| ISO main – ABC+ A- | | | |
| Is A a blicket? | Is B a blicket? | Is C a blicket? | Is D a blicket? |
| 0 | +1 | +1 | N/A |
| ISO control – ABC+ D- | | | |
| Is A a blicket? | Is B a blicket? | Is C a blicket? | Is D a blicket? |
| +1 | +1 | +1 | 0 |

It should be clear from the table above that this account predicts that for the BB main trials children should say that object A is a blicket significantly more often than either B or C but that their treatment of B and C should not differ. This is because objects B and C would have been paired with the machine exactly once, whereas object A would have been paired with the machine twice. Similarly, this account predicts that during the BB control trials participants’ treatment of all four objects should not differ. This prediction results from the fact that all four objects would have been paired with the machine’s activation exactly once. In contrast, this account predicts that participants should not consider object A to be a blicket but should be split in their treatment of objects B and C because B and C would have been paired with the machine’s activation an equal number of times; in other words, the effect of seeing object A paired with the machine’s activation during the ABC+ trials should be exactly canceled out by the effect of seeing object A paired with the machine’s inactivation during the A- trials. Likewise, during the ISO control trials, this account predicts that participants should not consider object D to be a blicket but should be split in their treatment of objects A, B, and C.

**The present investigation**

The present investigation had three goals. The first goal was to determine whether 4-, 5-, and 6-year-olds could engage in BB reasoning when asked to reason about three and four objects. A second goal was to determine whether participants show evidence of BB reasoning when it is operationally defined as greater treatment of object B in the BB control condition compared to the BB experimental condition. A third goal was to gain greater insight into how—that is, by what underlying cognitive mechanism—children reasoned about the present events. Specifically, we wanted to determine which of the three cognitive mechanisms better accounts for children’s causal inferences in the present context. The ideal mechanism is one that explains all of the data rather than a subset of it. Finally, given that some previous research operationally defined BB reasoning as greater treatment of object B in the BB condition compared to the ISO condition, participants in the present series of experiments also experienced the ISO condition (in a between-subjects manipulation).

**Experiment 1**

Experiment 1 assessed 4-year-old children’s ability to engage in BB when asked to reason about three objects. Participants were introduced to a computer-animated machine called the “blicket detector” and were told that their task was to determine which objects make the machine activate—and thus represent blickets—and which objects do not make the machine activate. Following this brief introduction phase, participants received either two BB main trials and two BB control trials or two ISO main trials and two ISO control trials. Participants in both conditions are then asked to indicate whether the objects in each trial were blickets. In this experiment, only a single object was shown during the elemental portion of the BB experimental event. Participants were randomly assigned to the BB or ISO conditions.

**Materials.** The “device” used in the experiments presented here was a computer-animated version of the blicket detector. 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. In addition, a maximum of 4 differently colored circles were used, and each circle measured 2.67 cm × 2.67 cm (INCLUDE FIGURE OF MACHINE AND TOYS). The machine was designed such that it activated immediately when a circle that was predetermined to be a blicket contacted it. At the start of any given trial, three (for the BB experimental trials) or four equally-spaced (for the BB control trials) circles appeared above the blicket machine. Finally, the videos contained a built-in script, which experimenters were instructed to read to ensure that all participants received exactly the same instructions and received the same text throughout the experiment. All video events were created in Microsoft PowerPoint.

**Procedure.** Participants were either tested in a quiet room on campus or 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 that were used during the main portion of the experiment. The pretraining phase began with the triangle (object A) and pentagon (object B), which were located side-by-side and above the machine. 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 ascended until it 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 the machine, which immediately activated. Participants were then asked whether each object was a blicket. This event was identical to the “one-cause” event in Gopnik, Sobel, Schulz, and Glymour (2001) and was included to ensure that participants could reason about blicket objects.

Following the pretraining phase, participants were given four test trials—either the two BB experimental trials and 2 BB control trials or two ISO experimental trials and 2 ISO control trials—in counterbalanced order using a Latin square. It should be noted that differently colored objects were used across all trials. This meant that no two events overlapped in the colors (for the objects) that were used.

The two BB 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 ascended 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; that is, 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 BB experimental trials were identical except that different colors were used for the objects.

The two BB 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 then descended by itself until it contacted and activated the machine. Children were then asked whether each object was a blicket. Note that object A descended with the remaining two objects in the BB experimental trials, whereas object D did not descend with the remaining three objects in the BB control trials. This means that D’s causal status should have no bearing on participants’ treatment of objects A-C. Note also that the BB control trials used the same text as the BB experimental trials. The first and second BB control trials were identical except that different colors were used for the objects.

Finally, the ISO experimental and control conditions were identical to the BB experimental and control conditions except that objects A (during the ISO main trials) and D (during the ISO control trials) failed to activate the machine. The schematic for this experiment is shown below in Table 1.

|  |  |  |  |
| --- | --- | --- | --- |
| Schematic of Experiment 1 | | | |
|  | Compound | Elemental | Test |
| BB experimental trial | ABC+ | A+ | Is A/B/C a blicket? |
| BB control trial | ABC+ | D+ | Is A/B/C/D a blicket? |
| ISO experimental trial | ABC+ | A- | Is A/B/C a blicket? |
| ISO control trial | ABC+ | D- | Is A/B/C/D a blicket? |

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

**Results**

All analyses were conducted in R (R Development Core Team, 2008). All *p* values were supplemented with Bayes Factors. *BF*H1 quantifies support for the alternative hypothesis compared with the null hypothesis. *BF*s close to 1 indicate equal support for both hypotheses, whereas *BFH0*s≥ 3 and < 10 indicate moderate and strong evidence for the alternative hypothesis, respectively (Lee & Wagenmakers, 2014).

**[Add Exp. 1 results here]**

**Discussion**

[INSERT EXPERIMENT 1 DISCUSSION HERE]

**Experiment 2**

Experiment 2 was similar to Experiment 1 except that 5- and 6-year-old children were tested.

**Method**

**Participants.** Participants were X 5-year-olds (X boys and X girls; *Mage* =X months, range = X-Y) and X 6-year-olds (X boys and X girls; *Mage* =X months, range = X-Y). 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 children’s museum.

**Materials & Procedure.** The materials and procedure for Experiment 2 was identical to that for Experiment 1.

**Results**

**Chart, bar chart

Description automatically generated**

Figure 3 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 1. Using this dependent measure, the data were entered into a five-way linear model with Age (5-year-olds vs. 6-year-olds) as the between-subjects factor and Condition (BB vs. ISO), Trial Type (experimental vs. control), and Objects (A vs. B vs. C vs. D) as the within-subjects factors. This analysis revealed a main effect of Condition, *F*(1, 548) = 12.68, *p* < .001, a main effect of Objects, *F*(3, 548) = 5.70, *p* < .001, a main effect of Event Type, *F*(1, 548) = 13.05, *p* < .001, and a significant interaction between Condition and Objects, *F*(3, 548) = 9.28, *p* < .001. This significant two-way interaction was qualified by a significant three-way interaction among Condition, Event Type, and Objects, *F*(2, 548) = 9.67, *p* < .001.

We followed up this three-way interaction with separate one-way linear models for the main and control trials within the BB and ISO conditions. The Objects factor was treated as the sole within-subjects factor in these follow-up analyses. The first one-way linear model for the control trials within the BB condition did not reveal a significant effect of Objects, *F*(3, 217) = 0.63, *p* = .59. This means that participants treated the objects similarly during the control trials of the BB condition. In contrast, the second one-way linear model for the main trials within the BB condition revealed a significant main effect of Objects, *F*(2, 159) = 3.63, *p* = .03. This main effect reflected the fact that participants considered object A marginally to be more of a blicket (*M* = 1.75, *SD* = 0.64) than object B (*M* = 1.47, *SD* = 0.77), *t*(52) = 1.92, *p* = .06, and significantly more of a blicket than object C (*M* = 1.37, *SD* = 0.83), *t*(52) = 2.5, *p* = .02.

The third and fourth one-way linear models for the main and control trials within the ISO condition both revealed a significant main effect of Objects, both *F*’s > 11.43, both *p*’s < .0001. This reflected the fact that participants considered object A (*M* = 0.57, *SD* = 0.89) to be significantly less of a blicket than objects B (*M* = 1.58, *SD* = 0.78) and C (*M* = 1.62, *SD* = 0.71) during the main condition, both *t*’s > -4.14, both *p*’s < .0001, and object D (*M* = 0.83, *SD* = 0.75) to be less of a blicket than objects A (*M* = 1.73, *SD* = 0.67), B (*M* = 1.66, *SD* = 0.67), and C (*M* = 1.63, *SD* = 0.61) during the control trials, all *t*’s > -4.74, all *p*’s < .0001.

**Assessing BB under the new operationalization of BB reasoning**

To examine whether there was evidence of BB reasoning under the new operationalization—in which participants’ treatment of some of the redundant causes is compared to their treatment of other redundant causes *within* the BB condition—data for the redundant causes within the BB experimental and control conditions were entered into a two-way linear model with Objects (A, B, and C) and Trial Type (main vs. control) as the within-subjects factors. This analysis revealed only a main effect of Trial Type, *F*(1, 267) = 5.26, *p* = .02, which reflected the fact that participants gave more “Yes” responses during the control trials (*M* = 1.67, *SD* = 0.63) than during the main trials (*M* = 1.42, *SD* = 0.80). Crucially, neither the main effect of Objects, *F*(2, 267) = 0.44, *p* = .64, nor the interaction between Objects and Trial Type*, F*(2, 267) = 0.44, *p* = .64, was significant. This reflected the fact that participants treated the redundant causes equally within the BB main and control conditions.

**Assessing BB under the old operationalization of BB reasoning**

To examine whether there was evidence of BB reasoning under the old operationalization—in which participants’ treatment of some of the redundant causes is compared to their treatment of other redundant causes *between* the BB and ISO conditions—data for the redundant causes between the BB and ISO conditions were entered into a two-way linear model with Objects (A, B, and C) and Trial Type (main vs. control) as the within-subjects factors. Similar to the analysis above, the only main effect was Trial Type, *F*(1, 400) = 4.47, *p* = .04, which reflected the fact that participants’ blicket ratings were higher during the control trials (*M* = 1.67, *SD* = 0.63) than during the main trials (*M* = 1.42, *SD* = 0.80). Crucially, neither the main effect of Objects, *F*(2, 400) = 0.53, *p* = .59, nor the interaction between Objects and Trial Type*, F*(1, 400) = 0.04, *p* = .83 was significant. These latter resulted indicated that participants treated the redundant causes equivalently between the BB and ISO main and control trials. Thus, these results indicate that participants neither engaged in BB reasoning under either the new or old operationalizations of it.

Discussion

Taken together, these results suggest that when participants are asked to reason about three and four objects—which corresponds to hypothesis spaces that consist of 8 and 16 candidate causal hypotheses, respectively—they do not engage in BB reasoning. Critically, are neither consistent with the predictions of a Bayesian-inference mechanism nor are they consistent with the predictions of the traditional RW model. Instead, the present results suggest that a simple associative-learning counting mechanism may have subserved participants’ performance in the present context. This is because such a mechanism fully accounts for the present data from both the 4-year-olds and the 5- and 6-year-olds. present results are not consistent with the predictions if BB reasoning is used as an indirect measure of the operation of a Bayesian-inference mechanism, then these findings are inconsistent with the notion that children use such a mechanism to reason about three objects.

General Discussion

This study had three aims. The first aim was to examine whether 4-, 5-, and 6-year-olds would engage in BB reasoning when asked to reason about 3 and 4 objects. This study departs from previous research on BB reasoning in which children were asked to reason about two potential causes (e.g., Beckers et al., 2009; Griffiths et al., 2011; Sobel et al., 2004). The second aim was to determine whether participants would engage in BB reasoning either under the older operationalization of it or under the newer operationalization of it. The third aim was to clarify the debate on *how* children reason about causal events in a BB context by assessing whether their performance aligned with the predictions of a simple Bayesian model, the traditional RW model, or an associative-learning counting mechanism.

In terms of the first two aims, there was no evidence that children engaged in BB reasoning when asked to reason about three or four objects. This was true regardless of how BB reasoning was operationalized. In other words, we neither found evidence of BB reasoning when we compared participants’ treatment of the redundant causes *between* the BB and ISO conditions nor did we find evidence of BB reasoning when we compared participants’ treatment of the redundant causes *within* the BB condition itself. This finding extends previous research to show that when participants are asked to reason about three or more objects, they do not engage in BB reasoning (see below for a potential explanation for this incongruity).

In terms of the third aim, the present results neither provide support for a Bayesian-inference mechanism nor do they provide support for the traditional RW associative-learning model. This is because participants’ behavior did not align the predictions of either model. For example, both the traditional RW model and the simple Bayesian model predict that participants should be maximally confident that object D is a blicket after the BB control trials but should treat objects A-C equivalently. The present results were at variance with this prediction: Participants treated all four objects equivalently during the BB control trials.

The present results are consistent with a simple associative-learning counting mechanism, however. These results suggest that children’s willingness to say that an object was a blicket depended on the frequency with which that object was paired with the machine’s activation; the more frequently that the object was paired with the machine’s activation, the more likely children were to say that the object was a blicket.

One potential criticism of this study is that it should be interpreted with caution because the results are inconsistent with the findings from previous studies on BB reasoning in human children. Such previous research showed that children do engage in BB reasoning when asked to reason about two objects; the current study showed that children do not engage in BB reasoning when asked to reason about three objects. However, we believe that the present results extend (rather than are at odds with) such previous research to show that when children’s information-processing capacities are stretched, they may deploy simpler associative mechanisms in causal contexts like the present one. Indeed, although at the level of individual objects the difference between three and four objects is miniscule, by contrast the corresponding increase in 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—which is the approach that has been taken in most, if not all, contemporary studies on BB reasoning in human children (e.g., Beckers et al., 2009; Griffiths et al., 2011; Kloos & Sloutsky, 2013; McCormack et al., 2009; McCormack et al., 2013; Sobel & Kirkham. 2006; Sobel et al., 2004)—need only to represent and choose among *four* candidate causal hypotheses (i.e., 2n, where *n* is the number of potential causes). Four hypotheses may be within the information-processing capacities of 4- to 6-year-olds. In contrast, children who are asked to reason about three or four candidate causes must now consider *eight* or *sixteen* candidate causal hypotheses, respectively. Eight and sixteen hypotheses may well be outside the limits of their restricted information-processing capacities for the developing child.

A considerable body of research with human children is consistent with this general thesis. For example, research that has used the Dimensional Change Cart Sort task—in which 3- and 4-year-old children are asked to sort cards first by one rule and then by another competing rule—will succeed on this task if the rules are consistent (e.g., ) but will fail (by relying on a first rule when asked to use a second rule, which is an ostensibly simpler strategy that is less cognitively effortful) if the rules are inconsistent and require children to inhibit one rule to use another rule (Doebel & Zelazo, 2015; Frye, Zelazo, & Palfai, 1995; Zelazo, Frye, & Rapus, 1996; Zelazo, Müller, Frye, & Marcovitch, 2003). Similarly, a recent study by Kenderla and Kibbe (2023) showed that when the information-processing capacities of 8- and 10-year-old children were stretched in a virtual memory game—such as when children were asked to find three cards that share one feature and differ on another feature—they relied less on working memory and more on manual exploration. Given that manual exploration does not require that participants actively maintain information in memory, manual exploration is ostensibly a simpler, less cognitively effortful strategy than one that requires 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 a salient distractor was made to compete with the critical relation 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 (e.g.,) and social-problem-solving tasks is adversely affected when they are first made to complete 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 BB 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 gofrom using a simple associative-based counting mechanisms in contexts like the present one to more rationale processes like Bayesian inference. Although this issue remains unaddressed to our knowledge, ongoing work in one of our labs that is using a task that is similar to the present one is showing that the causal inferences of adults are consistent with the predictions of a simple Bayesian model rather than the traditional RW model or a simple associative-based counting mechanism. Thus, there is reason to believe that sufficient information-processing capacities may be necessary for Bayesian inference and BB reasoning, and data by McCormack, Simms, McGourty, and Beckers (2013) seem to support this.

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 a priori that blickets were common in the present context—which is plausible given that the detector activated much more frequently in the present study than in previous studies on BB reasoning in children (e.g., Sobel et al., 2004)—then participants should be *less* likely to block redundant causes; in other words, participants should be *more* likely to treat candidate blickets equally. This could explain participants’ performance in the BB control condition—in that condition, participants treated all objects equally. However, we reject this explanation for two reasons. First, this explanation predicts that participants should have also treated objects A-C equivalently in the BB experimental condition as well, but this was not the case for any of the age groups: Participants treated object A differently than either objects B or C in the BB experimental condition. We also reject this explanation given that the performance of the 4-year-olds and the 5- and 6-year-olds was equivalent. If important prerequisites for Bayesian inference include the presence of sufficient information-processing capacities and sensitivity to base-rate information as we (and others; e.g., McCormack et al., 2013) have suggested, then the 4-year-olds should have performed differently than the 5- and 6-year-olds. This is presumably because 4-year-old children possess less robust information-processing capacities than 5- and 6-year-olds (e.g., Richland et al., 2006). This was not the case.

Nonetheless, because we did not systematically manipulate base-rate information, this alternative explanation cannot yet 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 shown to be affected by base-rate information, such that their BB reasoning performance changes with changes to base-rate information, then this would suggest that participants may use Bayesian inference to reason about multiple candidate cause after all, at least when base-rate information is explicitly and systematically manipulated. Thus, by examining whether participants are sensitive to base rate information in a BB context like the present one with multiple potential causes, we can provide even greater insight into the underlying causal mechanism that supports causal judgements in human children.

**Conclusion**

These potential criticisms notwithstanding, these experiments constitute one of the first systematic attempts to examine BB and IS reasoning in human children in the context of multiple 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 such as those captured by the traditional RW model (Rescorla & Wagner, 1972). The experiments reported here support a different conclusion. These results suggest that an associative-learning counting mechanism supports 4- to 6-year-old children’s reasoning about multiple potential causes in a BB context. Based on these results, we think that the conclusion that associative learning does not underpin causal reasoning in children may be premature.