Appendix

On a Bayesian-inference account, it is assumed that at the beginning of a learning task an ideal Bayesian learner represents all possible candidate hypotheses, *H*, whereby each hypothesis, *h* ∈ *H*, is assumed to have some prior probability, *p*(*h*), that is associated with it. This prior probability represents the learners’ confidence that the observed data were generated by a given causal hypothesis. Following observations of data, *d*, the learner then 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 is a normalizing constant that ensures that sum of the posterior probabilities is 1.

Given that Bayesian inference operates over a fixed hypothesis space, it is also important to specify the hypothesis space *H* and the hypotheses *h* that comprise that space for the present context. This step is necessary before Bayes' rule can be used to determine the hypothesis with the largest posterior probability. Given that participants were asked to reason about three objects in the present study, the hypothesis space consists of eight hypotheses. The specific parameterization of each hypothesis in the space is specified by the activation law, which, for all three experiments, states that the blicket detector will activate if, and only if, a blicket object contacts it. The second step in defining this model is to specify the prior probabilities of each hypothesis in each of the three experiments. If we assume that the probability that a particular object is a blicket is independent of the probability that other objects are blickets, then prior probabilities for these experiments can be found in Table X. Once we have specified the prior probabilities, it is possible to use them to compute the posterior of each hypothesis when new data is observed, according to Bayes' rule.

Given that the present experiments used deterministic causes, that either did or did not activate the machine, whenever a link exists in the model and the data are consistent with that link, the likelihood of a particular hypothesis is set to 1; whenever a link does not exist the likelihood is set to 0. Once it is determined that a link exists for a particular object, we can compute the likelihood that the objects are blickets by taking the product of the likelihood that a particular object activated the detector under each hypothesis and the prior probability of each hypothesis and then summing this product. To determine the probability that object B is a blicket, for example, we can compute the following equation:

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