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*Research*

# The power of possibility: causal learning, counterfactual reasoning, and pretend play

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We argue for a theoretical link between the development of an extended period of immaturity in human evolution and the emergence of powerful and wide-ranging causal learning mechanisms, specifically the use of causal models and Bayesian learning. We suggest that exploratory childhood learning, childhood play in particular, and causal cognition are closely connected. We report an empirical study demonstrating one such connection—a link between pretend play and counterfactual causal reasoning. Preschool children given new information about a causal system made very similar inferences both when they considered counterfactuals about the system and when they engaged in pretend play about it. Counterfactual cognition and causally coherent pretence were also significantly correlated even when age, general cognitive development and executive function were controlled for. These findings link a distinctive human form of childhood play and an equally distinctive human form of causal inference. We speculate that, during human evolution, computations that were initially reserved for solving particularly important ecological problems came to be used much more widely and extensively during the long period of protected immaturity.

**Keywords:** causal reasoning; counterfactual reasoning; pretence; cognitive evolution; developmental psychology

## 1. INTRODUCTION

The great puzzle of the evolution of human cognition is to determine how such small genetic changes over such a brief period could have led to such massive changes in behaviour. In this paper, we emphasize two interlocked developments that might have interacted in a coevolutionary way to provide large differences from small changes. The first is the change in the developmental program that led to the uniquely long period of human childhood. We hypothesize that this change allowed immature proto-humans to enjoy longer protected periods of learning and, in particular, to engage more extensively in the free exploration found in play.

Second, we propose that this developmental change created the context for the application of more powerful learning mechanisms. In particular, these learning mechanisms included a newly sophisticated and general ability and motivation to learn about causation and to construct causal models. Those models, in turn, support sophisticated inference and planning by allowing organisms to consider a wide range of

alternative possible future outcomes. The result was a set of new abilities including more sophisticated tool use for foraging and more sophisticated social intelligence for cooperative child-rearing. Those abilities, in turn, allowed for still greater caregiving investment and a still longer childhood and so on.

In the first part of this paper, we discuss some of the theoretical ideas underlying this proposal that childhood learning, and play in particular, and adult causal cognition are closely connected. In the second part, we focus on an empirical study demonstrating one such connection—a link between pretend play and counterfactual causal reasoning. We show that children who are given new information about a causal system make very similar inferences both when they consider counterfactuals about the system and when they engage in pretend play about it. We also show that these two abilities are correlated—children who apply appropriate causal constraints in their pretend play also do better in a counterfactual task. This relationship holds even when age, general cognitive development and executive function are controlled for. These findings link a distinctive human form of childhood play and an equally distinctive human form of causal inference.

This study is just one example of a more general link between learning and behaviour in childhood and adult cognitive abilities. However, we believe it is a particularly telling one. We argue that the free

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exploration of possibility in pretence helps human beings to construct wide-ranging causal models of the world and to reason from them.

## 2. THE USES OF IMMATURITY

There is strong evidence that a change in the developmental program played an important role in human evolution. Human offspring, in particular, have a longer period of immaturity than those of any other primate. This is also true of *Homo sapiens* when compared with extinct hominoids, such as Neanderthals [1]. The cost of protracted immaturity is the need for greater caregiving, and here too, humans show striking adaptations for increased caregiving investments in comparison with our closest primate relatives, including pair bonding, increased alloparenting and a long period after menopause (the ‘grandmother’ hypothesis [2,3]).

There is, moreover, a widespread correlation between extended immaturity, relatively large brain size and relatively sophisticated learning abilities across many species, including birds, placental and marsupial mammals [4]. The extreme immaturity and impressive brain size and learning ability of humans lie at the far end of the distribution on these measures.

These correlations suggest a connection between the cognitive changes in humans and the extended period of human development. But how might one lead to the other? It is possible, of course, that longer immaturity was necessary simply to have the time to grow large brains. But it is equally possible, and arguably more plausible, that our evolutionary advantage accrued from the fact that during development those brains were being modified and shaped under the influence of the environment, and in a way that allowed massive plasticity and learning [5]. The revolution in cognitive development over the past 30 years has shown that infants and very young children do, in fact, engage in just this kind of learning. While in the past it may have been possible to think of infants and young children as cognitively limited creatures who simply passively waited for brain maturation, contemporary research demonstrates that even infants and toddlers learn a remarkable amount in remarkably sophisticated and complex ways (for recent reviews, see [6,7]).

Young children not only learn as much or more than adults, they also learn differently. In the language of machine learning, there is a trade-off between ‘exploration’ learning, learning about the environment for its own sake, and ‘exploitation’ learning, finding the right information about the environment to achieve a particular goal. ‘Exploration’ learning is wide-ranging and general, and has many advantages—it allows organisms to discover methods for survival in a diversity of physical and social environments. It also has some disadvantages. In particular, it means that organisms will not be prepared to deal with the particular demands of the environment until after learning has taken place. We argue that extended immaturity helps resolve that trade-off—a protected period of exploration as children allows us to exploit as adults. Empirically, young children do engage in extensive exploratory learning. Immaturity allows

powerful and varied exploratory learning mechanisms to be extensively employed in the protected period of human childhood, while the costs of everyday survival are borne by carers.

What do those learning mechanisms look like? One likely candidate is a set of computational devices for learning about the causal structure of the world. The ability to understand causal relationships and to reason from them is at the heart of many distinctive human abilities. Understanding physical causal relations underpins sophisticated forms of tool use [8,9]. Understanding psychological causal relations underpins the ability to understand and manipulate others, abilities that are at the core of ‘theory of mind’ or ‘Machiavellian intelligence’ [10]. Causal understanding thus underpins the kinds of cognition that have been proposed as part of the distinctively human cognitive toolbox. Moreover, in both the physical and psychological domains, causal knowledge allows for sophisticated inferences about the future and about the counterfactual past. Such thinking has been called ‘mental time travel’ [11–13]. All of these abilities are clearly present in nascent form in some non-human animals, but there is little doubt that these are dimensions where humans are distinctively capable.

## 3. CAUSAL MODELS AND BAYESIAN LEARNING

Recent work has outlined the kinds of representations that underpin causal knowledge in adult humans and the kinds of mechanisms that allow this knowledge to be learned [14–16]. This work is part of a broader approach to cognition that involves probabilistic models and Bayesian inference [17]. The essential idea behind this recent research is that humans have *causal models*: structured, generative, causal representations of the world. These representations appear to go beyond the typical representations that might be constructed from simple associative processes or conditioning.<sup>1</sup>

What makes causal models distinctive? Traditionally, philosophers and psychologists have had two approaches to causation. One approach focuses on ‘mechanisms’—on the particular spatio-temporal characteristics of events, particularly events that involve contact or launching [22]. However, many events that do not include these features, ranging from remote controls to social interactions, are also construed as causal even by very young children [23]. Another tradition, going back to Hume, is that causal relations are nothing more than associations between correlated events. But if the mechanism approach is too narrow, the correlational approach is too wide. A causal relationship goes beyond a predictive or associative one, as we outline below.

More recently, philosophers have pointed to two distinctive features of causal knowledge, which are captured by causal models. First, causal knowledge supports a distinctive set of inferences involving interventions and counterfactuals [15,24–26]. For example, both smoking and having yellow nicotine-stained teeth are associated with lung cancer. So if you see yellow teeth, you can predict the presence of cancer. However, only a causal account of the disease

leads to the correct prediction that a tooth-brushing intervention will have no effect on the cancer rate, while a smoking-prevention intervention will. Similarly, causal knowledge supports counterfactual claims [27]. A causal account of cancer will also tell you that, had smoking been discouraged in the past, many lives would have been saved.

Second, causal knowledge involves not only specific relations between particular causes and effects, but coherent networks of causal relations—the kinds of networks that are described in theories. In operant conditioning, or in trial-and-error learning, a learner must previously observe the effects of an action or a series of actions in order to predict those effects in the future. This is not the case for a learner with a causal theory, who can predict the effects of such actions without ever having observed them. In fact, these actions might be quite unusual and have a low initial probability. Causal theories thus allow reasoners to make a very wide range of new predictions, interventions and counterfactual inferences about events, allowing for sophisticated kinds of insightful planning and action.

For example, a scientist could use a physical causal theory to predict that the very complex and novel sequence of actions involved in the Apollo 11 launch would result in the unprecedented event of a man walking on the moon. But we also see this coherence in intuitive or everyday theories, not just in scientific ones. Children 2 and 3 years old, for example, appear to have a causal theory of the mind—they can appreciate the complex causal relations between emotions, perceptions and desires, and can use these relations to generate novel explanations and inferences about events they have never experienced before [28].

Formal models of causal relationships, such as causal graphical models, represent these causal networks as graph structures associated with probability distributions [24,25]. They also include procedures for making predictions, designing interventions and making counterfactual claims. Specifically, in both interventions and counterfactuals, the learner ‘fixes’ the value of a variable in a causal network. Then she uses the model to work out the ‘downstream’ consequences in the possible world where the variable had that value. If the consequences are desirable, she can act to cause the variable to have that setting in the actual world—she can produce an intervention. But she can also simply consider what would have happened if the variable had been set to that value, and so think of the counterfactual consequences of an event or an action. There is extensive evidence suggesting that both adults and children can use causal models in this way to make predictions and design interventions, and that adults can use them to make counterfactual inferences about the past [14,29–32].

Causal models thus allow their users to make a powerful range of new predictions. Equally importantly, causal models can be learned, and lend themselves to Bayesian learning mechanisms [17,33]. Such mechanisms involve searching through a space of possible hypotheses—in this case, possible causal models—and comparing them to the evidence.

Obviously, it is not possible to simply enumerate and assess all the possible hypotheses individually. But Bayesian learning algorithms can approximate that search. For example, a Bayesian learning strategy might proceed by starting with the current best model for how the world works. In order to learn, a user must modify that model to produce an alternative, and then assess the fit between the evidence generated by this alternative model and the actual evidence observed in the real world. This assessment is done by calculating the probability that the alternative model would generate the observed evidence. This involves asking two questions: (i) How probable is it that one would observe these events if the alternative model was a true representation of the causal structure of the world? (ii) How likely is the causal relationship that this model represents overall, taking into account its prior probability? The user must also answer these questions about his or her current model. If the resulting probability of the alternative model is higher, the user should discard the current model and accept the alternative model as true. There is evidence that human children as young as 16 months old can learn causal models from statistical information in this way [14,34–36].

This learning procedure, like other Bayesian procedures, is powerful, but it is computationally demanding. It requires that the learner explores a range of possible models before settling on the most likely one. But we believe that even this kind of complex computation and comparison is within the grasp of preschool-aged children. Indeed, we see exactly such exploration of alternative models emerging spontaneously and early in children’s pretend play.

#### 4. PRETEND PLAY

Play is characteristic of young animals across a wide range of species [37]. The behaviours that are involved in play are typically those that will be important for the adults of the species, which explains why play fighting and hunting behaviours are ubiquitous. Play is a form of exploratory learning. The immature animal can explore and practise alternative actions in a low-risk setting, without the pressure of achieving a particular goal. Indeed, a striking recent programme of research shows that a distinctive kind of exploratory play that involves informal experimentation helps human children learn causal models, supporting the idea of an evolutionary connection between childhood play and causal learning [38,39].

However, human children also engage in a particularly distinctive kind of pretend or symbolic play. In this type of play, children go beyond simply practising actions they will require later or manipulating objects to discover their causal features. Instead, they work out quite elaborate unreal scenarios, often with the aid of language, props and gestures. As with so many human behaviours, there is evidence that precursors of this kind of play may be found in other primates, particularly symbol-trained chimpanzees [40]. However, again as with many other behaviours, it is clear that this is a domain where humans are at least quantitatively if not qualitatively different. In all her hours of

observation of the chimpanzees of Gombe, for example, Jane Goodall only recorded a few instances of what might have been pretend play. In contrast, almost any observation of 4-year-old humans would uncover multiple instances of such play [41–44], and human children demonstrate remarkable competence not only at pretending but at understanding the rules that govern pretence (see [45] for a review). Indeed, though cultures may vary in the amount and the themes of early pretend play, such play is found across a strikingly wide variety of cultural settings [46]. But pretend play also has a paradoxical quality. Why would children spend so much time and energy engaged with non-real scenarios when it would arguably serve them better to attempt to understand how the real world works?

Our answer to this question focuses on the similarities between the playful activity of pretending and the serious reasoning capabilities involved in counterfactual inference and Bayesian learning [47]. A number of researchers have previously remarked on the similarities between play and counterfactual inference [48–51]. But simply noting these similarities does not explain why counterfactual reasoning itself would be useful, given that it is also about possible worlds rather than actual ones. In addition, to our knowledge, there have been no previous empirical demonstrations that pretence and counterfactual reasoning are specifically related in development.

We address the first issue by proposing that pretend play provides an opportunity to practice and perfect the skills of reasoning from, and learning about, a causal model, just as play fighting or hunting allows animals to perfect complex motor skills. Pretend play, counterfactual and intervention reasoning, and Bayesian learning all involve the same cognitive machinery: the ability to consider events that have not occurred, in Leslie's terms, to 'decouple' representations of those events from reality [43] and to think about what would be the case if they had occurred [52]. These abilities are required not only for planning, but also for learning. In order to execute the algorithms that are involved in Bayesian causal learning, children need to do the same things they do when they pretend. They must create an alternative representation and generate the observations that they would have seen if that alternative were true. Just as physical play provides young animals with the opportunity to practice skills that they will need later in life, we argue that pretend play lets children practice the cognitive skills necessary for causal learning, planning and counterfactual reasoning.

Preschool children are especially focused on developing causal models of the minds of others or a 'theory of mind'. Accordingly, much early pretend play, such as the creation of imaginary companions, is also focused on exploring these kinds of psychological causal relationships [47]. There have been both theoretical and empirical claims about the relation between pretend play and theory of mind abilities [43,51,53]. However, preschoolers also learn physical causal models. We thus predict that children's abilities to make physical causal inferences should also be related to pretence.

How could we test this claim? There is already evidence in the literature that children typically obey causal constraints in their pretence [49]. For example, if children are given a pretend scenario in which Teddy spills tea on the floor, they will infer that the floor is wet, but they will say that it is dry if he spills talcum powder. There is also some evidence that children as young as 2½ years can make counterfactual inferences, although this is more controversial [42,49,54]. Faced with a floor with muddy ducky bootprints, for example, children will say that the floor would have been clean if ducky had taken his boots off [42,49].

In both of these cases, however, children might be interpreted as simply following familiar and highly practised scripts rather than making novel inferences. Children know that tea spilling is followed by wetness, just as a young wolf might know that mock biting follows mock chasing. Moreover, there is no current empirical evidence that these two abilities, causal constraint in pretence and counterfactual inference, are actually connected to one another.

Here, we present the first empirical evidence of this connection. We presented children with a novel causal system and taught them a novel causal relationship, ensuring that children were not simply reproducing a familiar script. We then tested whether they would import the causal structure into their pretend play, whether they would make the correct counterfactual causal inferences about that system, and whether these two abilities were related. This study thus provides us with a way to explore the proposed relationship between causal and counterfactual reasoning and pretence.

## 5. EXPERIMENT 1

In this experiment, 3- and 4-year-olds were taught a novel causal relationship and then were encouraged to engage in a pretend game to see if they would maintain and act on this relationship in the context of an imaginary world. The causal relationship involved a toy, the 'Birthday machine,' which plays 'Happy Birthday' when an object called a zando is placed on top, but which does not activate with a non-zando object. The toy was actually surreptitiously activated by a hidden button, a commonly used method in causal-learning tasks. Indeed, in extensive other experiments using this and similar 'detector' machines, both children and adults inferred a causal relation between the objects and the effect—no child or adult ever guessed the hidden cause [55]. Moreover, in similar experiments, preschool children could acquire a causal model of such machines that allowed them to make novel inferences about interventions on the machine and to explicitly infer its causal structure, even when that causal structure was complex [14,29,56–58].

During our study, we told children that it was a stuffed toy named Monkey's birthday, and that the experimenter and the child would use the 'Birthday machine' to sing to Monkey as a surprise for his birthday. The experimenter taught the child the causal relationship and then asked him/her a series of counterfactual questions about the machine.

Then a confederate entered the room and removed the machine, the zando and the non-zando object. In response, the experimenter introduced a box and two blocks and explained that they could still surprise Monkey if they pretended that the box was the machine and that one block was the zando and the other was the non-zando. The experimenter first asked the child what he or she wanted to pretend. Then the experimenter prompted the child to try each block on the machine and asked him/her what they were pretending was the consequence of this action, to see if the child would uphold the real-world causal relationship she/he had learned in the context of the pretend game.

Based on our hypothesis that children's pretend play facilitates counterfactual causal reasoning, we made several predictions. First, we predicted that children would transfer the real-world causal relationship into the pretend scenario. That is, children should intervene with the pretend zando to bring about pretend music, and have the pretend non-zando be causally ineffective. We further predicted that children who made this transfer in pretence would be more likely to answer the real-world counterfactual questions correctly.

## 6. METHOD

Fifty-two 3- and 4-year old children were tested in this study (see the electronic supplementary material for details).

### (a) *Causal demonstration phase*

The experimenter began by explaining to the child that today was her friend Monkey's birthday and that the goal of the game was to surprise Monkey. The experimenter then put Monkey underneath the table so that he would be unable to hear what the surprise was. The experimenter then introduced the 'Birthday machine' to the child by saying, 'This is my machine. And you know what? This machine plays 'Happy Birthday'.' The experimenter explained that the surprise would be to sing 'Happy Birthday' to Monkey when the machine played the song. The experimenter then placed two distinctive objects on either side of the machine in counter balanced order, and said 'One of these is a zando and one is not a zando. The machine *only* plays 'Happy Birthday' when the zando is on top, so I'm going to need your help to figure out which of these objects is the zando.'

The experimenter then placed each object on the machine twice. Afterwards, the child was asked to identify which object was the zando. If the child made an incorrect selection, the demonstrations were repeated. After making his/her selection, the child was allowed to place each object on the machine himself/herself.

### (b) *Counterfactual phase*

In this phase, the experimenter asked a counterfactual question about each object. For the zando, the experimenter asked, 'If this one were not a zando, what would happen if we put it on top of the machine?' For the non-zando, the experimenter asked the opposite question (i.e. 'If this one were a zando...?'). The

order of the questions was counterbalanced across participants. If the child did not respond, the experimenter asked a forced-choice question: 'Would the machine play music or not play music?' The experimenter then suggested that the child put the zando on top of the machine one more time to practise singing for Monkey.

### (c) *Pretence phase*

In this phase, a confederate entered the room and said that she needed to borrow the machine. The confederate removed the machine, zando and non-zando from the room. The experimenter expressed sadness that the confederate had taken the machine before they could surprise Monkey. She then said that she had an idea, and brought out a white wooden box and two coloured blocks. The experimenter explained, 'I thought we could pretend that this box is my machine and that this block (one of the coloured blocks) is a zando and that this block (the other coloured block) is not a zando. Then, we could still surprise Monkey!' (Which coloured block was the zando as well as the side of presentation of the blocks was counterbalanced across participants.) The experimenter then took Monkey out from underneath the table and asked the child what they should pretend in order to make the pretend machine play music. At this point, the child could place either block onto the machine. If the child did not choose a block, the experimenter asked, 'Which of these should we try to pretend to make the machine play music?' Once the child placed a block on top of the machine, the experimenter asked, 'What are we pretending now?' If the child did not offer a response, the experimenter asked, 'Are we pretending music or no music?' The experimenter then suggested that they try the other block, and repeated the procedure.

After the child had tried each block on the machine, the experimenter said that she had another idea. She reversed the pretend roles of the blocks so that the original pretend zando was now the pretend non-zando and the original pretend non-zando was now the pretend zando. The experimenter then asked, 'Now, what should we do to pretend to make the machine play music?', and repeated the same series of questions as before with the new pretend zando and pretend non-zando.

### (d) *Coding*

For the counterfactual and pretence questions, if children's answers indicated that music was playing, such as 'Music', 'Yes', 'Happy Birthday', 'It works', or nodding their head, their answer was coded as 'music'. If children's answers indicated that no music was playing, such as 'No Music', 'No', 'I don't hear anything', 'Nothing' or shaking their head, their answer was coded as 'no music'. If a child was too shy to produce a verbal response, then the experimenter assigned the option of 'music' to one of her hands and the option of 'no music' to the other hand and asked the child to point to a hand.

For the counterfactual questions, children's answers were considered correct if they could be coded as 'no

music' for the question about the zando being a non-zando and as 'music' for the question about the non-zando being a zando. For the pretence questions, children's answers were considered correct if their answer could be coded as 'music' for the pretend zando and 'no music' for the pretend non-zando. Finally, in the pretence phase, children's first choice for making the machine go was recorded (i.e. whether or not they chose to put the pretend zando or non-zando on the machine first). An independent coder re-coded 90 per cent of children's performances from videos of the experiment. There was excellent inter-coder agreement on both counterfactual performance (Cohen's  $\kappa = 0.94$ ), and pretence performance (Cohen's  $\kappa = 0.94$ ).

In addition to coding these formal measures, we also coded the degree and elaboration of the child's subsequent spontaneous pretence in the pretend scenario to ensure that children were actually pretending. An independent coder judged the extent of children's involvement in the pretend scenarios from videotapes of the test scenario and coded children's responses as falling into one of three categories, (i) no pretence beyond pretending about the effects of the zando, (ii) one or two spontaneous extensions of the pretence or (iii) extended spontaneous engagement in the pretence.

## 7. RESULTS

Preliminary analyses did not find any effect of gender, question order, side of presentation of the zando or block colour on responses to either the counterfactual or pretence questions, so these variables were not considered further.

### (a) Counterfactual phase performance

Children were given a counterfactual score of 0, 1 or 2 for the number of counterfactual questions they answered correctly, with chance performance being a score of 1 (table 1). Overall, children's performance on the counterfactual questions was significantly better than chance ( $M = 1.5$ , s.d. = 0.80,  $t_{51} = 4.48$ ,  $p < 0.001$ ).

Children also tended to answer the individual counterfactual questions correctly, saying that if the zando were a non-zando it would not play music when placed on the machine (exact binomial test:  $X = 42$ ,  $n = 52$ ,  $P = 0.5$ ,  $p < 0.001$ ), and if the non-zando were a zando then it would play music ( $X = 36$ ,  $n = 52$ ,  $P = 0.5$ ,  $p < 0.01$ ). Finally, consistent with previous findings, children's counterfactual performance was correlated with age,  $r_{50} = 0.33$ ,  $p < 0.05$ ; however, contrary to some earlier studies, both 4-year old and 3-year-old children were above chance (4-year olds:  $t_{25} = 4.47$ ,  $p < 0.001$ ; 3-year olds:  $t_{25} = 2.087$ ,  $p < 0.05$ ).

### (b) Pretence phase performance

Children were given a pretence score between 0 and 4 (with chance performance being a score of 2) for pretending that the appropriate effect followed a block being placed on the pretend machine—music playing for the pretend zando and no music playing

Table 1. Children's performance in the counterfactual phase of experiment 1.

no. correct answers	0	1	2
no. children	10	6	36

Table 2. Children's performance in the pretence phase of experiment 1.

no. correct answers	0	1	2	3	4
no. children	0	3	21	3	25

for the pretend non-zando for both the objects' original roles and their reversed roles (summarized in table 2). In general, children chose to intervene with the pretend zando block in order to cause pretend music ( $M = 1.69$ , s.d. = 0.51,  $t_{51} = 9.86$ ,  $p < 0.001$ ). They did so in both the original (exact binomial test:  $X = 48$ ,  $n = 52$ ,  $P = 0.5$ ,  $p < 0.001$ ) and reverse (exact binomial test:  $X = 40$ ,  $n = 52$ ,  $P = 0.5$ ,  $p < 0.001$ ) pretend scenarios. Overall, children said that their interventions in the pretend scenario had causal outcomes consistent with their effects in the real world ( $M = 2.96$ , s.d. = 1.1,  $t_{51} = 6.51$ ,  $p < 0.001$ ).

Children's pretence scores were marginally correlated with their age,  $r_{50} = 0.23$ ,  $p = 0.1$ . However, these scores were significantly correlated with their counterfactual scores,  $r_{50} = 0.62$ ,  $p < 0.001$ . The relationship between pretence and counterfactual scores remains significant even when controlling for age,  $r_{50} = 0.59$ ,  $p < 0.001$ .

Most of the children (71%) spontaneously elaborated the pretend scenario beyond the experimenter's questions and nearly half (44%) engaged in extended pretence, indicating that the children were indeed pretending. There was no difference in the counterfactual performance of children who demonstrated extended or elaborated pretence or simpler pretence. Examples of children's elaborations include extending the celebration of Monkey's birthday, such as having Monkey cover his eyes to receive his surprise, hiding the pretend machine to surprise Monkey, pretending that the box is a cake for Monkey, or that the blocks are presents for Monkey (e.g. the blocks are flowers, or 'hotwheels cars'). Children also spontaneously engaged in additional pretence about the machine, for instance, continuing to reverse the roles of the pretend blocks after the experiment had ended (e.g. 'How about now *this* one is the zando! Let's try it on the machine!'). Of particular note, a number of children engaged in novel causal interventions during the pretence that were never demonstrated with the real machine, for instance, placing both blocks on the box and announcing whether there was music.

## 8. DISCUSSION

Overall, children were able to respond correctly to counterfactual questions about a novel real-world

causal relationship. In the counterfactual phase of the experiment, children correctly reasoned that if the zando were not a zando it would not cause music, and if the non-zando were a zando it would cause music. Note that these are classical counterfactuals about possible worlds rather than questions that could be interpreted as future hypotheticals. This finding is especially impressive considering that both objects were not only visible but highlighted in this task, which could have made their actual causal roles salient and difficult to inhibit. Indeed, children had only ever seen the non-zando negatively associated with the effect. Nevertheless, they were able to infer that it would cause the music in the alternative world specified by the counterfactual premise.

Children were also able to maintain and intervene on this newly learned causal structure within a pretend scenario, making inferences consistent with the pretend objects' real-world causal roles, and acting on the pretend causal relationship to bring about a desired pretend outcome. In the pretence phase of the experiment, children's causal inferences about the pretend objects were consistent with the objects' real-world causal roles. When asked to make the pretend machine go, children chose to intervene with the pretend zando block, placing it on the pretend machine. Furthermore, they said that the pretend zando would lead to music, but that we should not pretend music for the pretend non-zando. This is striking because, given that this was a pretend world, children could simply have always pretended that the desirable outcome, playing 'Happy Birthday,' had occurred.

Finally, children were able to flexibly reassign the causal roles of objects within the pretence. They provided correct answers both about each object's original pretend role and about its reversed pretend role. This indicates that they are able to consider multiple alternative possible worlds.

While a majority of children answered both counterfactual questions correctly, 30 per cent answered at least one counterfactual question incorrectly (table 1) and a similar number failed to import the causal constraints to their pretence. In these instances, children tended to respond consistently with the object's real-world role, rather than its hypothesized role. In particular, these children would say that the zando block would continue to activate the machine even if it were not a zando, or, in the pretend case, that neither object would cause music.

Moreover, children's performance on the counterfactual questions correlated with their pretence performance, even when age was taken into account. This suggests a link between counterfactual reasoning abilities and pretence, consistent with our theoretical account of these abilities. However, while experiment 1 provides some evidence for a relationship between pretend play and counterfactual thinking, other explanations are possible. Although the relationship did not depend on age, general cognitive development might account for children's improvement on both tasks. Another possibility is that children who perform poorly on both tasks may have a difficult time inhibiting their real-world knowledge (as suggested by [59]).

Table 3. Children's performance in the counterfactual phase of experiment 2.

no. correct answers	0	1	2
no. children	11	12	37

In this case, children's executive function abilities would correlate with both their counterfactual and pretence success. We test these possibilities in experiment 2.

## 9. EXPERIMENT 2

In this experiment, we replicated the procedure from experiment 1 with the addition of a conservation task and an executive function task to gauge children's general cognitive and inhibition skills. We used the classic Piagetian conservation task, which involves rows of pennies that are stretched out and pushed together to see if children understand that the number of pennies does not change despite these physical transformations [60]. The Stroop-like executive function task that we used was the day–night task [61–63], which involved cards depicting daytime and nighttime. Children had to say 'day' when they saw a night-time card and 'night' when they saw a daytime card. (See the electronic supplementary material for details on the administration and scoring of these two tasks.)

Sixty 3- and 4-year-old children were tested in this study (see the electronic supplementary material for additional details). The tasks were administered in one of two orders counterbalanced across subjects: either (i) conservation, (ii) executive function, (iii) pretence, or (i) pretence, (ii) conservation, (iii) executive function. An independent coder re-coded 90 per cent of children's performances from videos of the experiment. There was excellent inter-coder agreement on both counterfactual performance (Cohen's  $\kappa = 0.92$ ) and pretence performance (Cohen's  $\kappa = 0.92$ ).

## 10. RESULTS

Preliminary analyses did not find an effect of gender, question order, which side of the machine the zando was placed on, or which colour block the pretend zando was on responses to either the counterfactual or pretence questions. These variables were not considered further.

### (a) Pretence task performance

#### (i) Counterfactual phase performance

As in study 1, children's performance on the counterfactual questions was significantly better than chance ( $M = 1.43$ ,  $s.d. = 0.79$ ,  $t_{59} = 5.56$ ,  $p < 0.001$ ; table 3). In general, children also answered the individual counterfactual questions correctly, saying that if the zando were a non-zando it would not play music when placed on the machine (exact binomial test:  $X = 45$ ,  $n = 60$ ,  $P = 0.5$ ,  $p < 0.001$ ), and if the non-zando were a zando then it would play music (exact binomial test:  $X = 41$ ,  $n = 60$ ,  $P = 0.5$ ,  $p < 0.01$ ). Children's counterfactual performance was correlated with age,



Table 4. Children's performance in the pretence phase of experiment 2.

	0	1	2	3	4
no. correct answers	0	1	2	3	4
no. children	1	4	12	14	29

$r_{58} = 0.40$ ,  $p < 0.01$ . Both 4-year old and 3-year-old children were above chance (4-year olds:  $t_{27} = 5.01$ ,  $p < 0.001$ ; 3-year olds:  $t_{31} = 2.48$ ,  $p < 0.05$ ).

#### (ii) Pretence phase performance

Children chose to intervene with the pretend zando block in order to cause pretend music ( $M = 1.67$ , s.d. = 0.51,  $t_{59} = 5.06$ ,  $p < 0.001$ ; table 4), in both the original (exact binomial test:  $X = 50$ ,  $n = 60$ ,  $P = 0.5$ ,  $p < 0.001$ ) and reverse (exact binomial test:  $X = 50$ ,  $n = 60$ ,  $P = 0.5$ ,  $p < 0.001$ ) pretend scenarios. Overall, children also said that their interventions in the pretend scenario had causal outcomes consistent with the real-world ( $M = 3.1$ , s.d. = 1.05,  $t_{59} = 6.62$ ,  $p < 0.001$ ): when they put the pretend zando on the machine, they said that this led to pretend music ( $M = 1.42$ , s.d. = 0.81,  $t_{59} = 5.59$ ,  $p < 0.001$ ), but when they put the pretend non-zando on the machine, they said that this did not lead to pretend music ( $M = 1.68$ , s.d. = 0.60,  $t_{59} = 4.11$ ,  $p < 0.001$ ). This was true in both the original ( $M = 1.55$ , s.d. = 0.57,  $t_{59} = 6.17$ ,  $p < 0.001$ ) and reverse ( $M = 1.56$ , s.d. = 0.62,  $t_{59} = 5.60$ ,  $p < 0.001$ ) pretend scenarios.

Children's pretence scores were significantly correlated with their age,  $r_{58} = 0.31$ ,  $p < 0.05$  and their counterfactual scores,  $r_{58} = 0.44$ ,  $p < 0.001$ . However, the relationship between pretence and counterfactual scores remains significant even when controlling for age,  $r_{58} = 0.36$ ,  $p < 0.01$ .

### (b) Secondary task performance

#### (i) Conservation task performance

Children were given a score between 0 and 3 for the number of conservation questions they answered correctly. As has been found previously, children's performance on this task varied considerably ( $M = 1.51$ , s.d. = 1.07), and is summarized in table 5. There was no correlation of conservation performance with age,  $r_{57} = 0.02$ ,  $p = 0.87$ , counterfactual score,  $r_{57} = 0.09$ ,  $p = 0.47$  or pretence score,  $r_{57} = 0.15$ ,  $p = 0.25$ .

#### (ii) Executive function task performance

Children received 16 trials and were assigned a proportion of correct answers. Overall, children performed better than chance ( $M = 0.61$ , s.d. = 0.25,  $t_{43} = 2.87$ ,  $p < 0.01$ ). As in previous work [61–63], there was variance in children's performance, including two children who got zero answers correct, and one child who answered all 16 cards correctly.

Children's performance on the day–night task was correlated with their age,  $r_{42} = 0.33$ ,  $p < 0.05$ . There was no correlation between performance on the day–night task and counterfactual score,  $r_{42} = 0.04$ ,  $p = 0.81$ , or pretence score,  $r_{42} = 0.05$ ,  $p = 0.76$ .

Table 5. Children's performance on the conservation task.

	0	1	2	3
no. correct answers	0	1	2	3
no. children	11	22	11	15

Moreover, the relation between the counterfactual score and pretence score remained significant even when executive function, age and conservation were all controlled for  $r_{44} = 0.38$ ,  $p < 0.05$ .

## 11. GENERAL DISCUSSION

In two studies, we found a relation between young children's ability to make counterfactual inferences and their tendency to use causal constraints in their pretend play. In principle, pretend play is unconstrained—children who wanted to make Monkey happy could have simply pretended that any block would make the machine go. In practice, however, children used the demonstrations that they observed to make inferences about situations they had never encountered, such as the counterfactual world in which the non-zando was a zando, or the world in which a plain box really was a 'Birthday machine'. Moreover, these abilities were specifically related, even controlling for age, general cognitive ability and executive function.

These results suggest a strong link between pretending and counterfactual reasoning abilities. In turn, this supports a relationship between the extended playful exploration enabled by a long period of childhood and the ability to deploy causal models to make counterfactual inferences in a wide-ranging and general way. Although our result itself is only correlational, its specificity does suggest some causal link between the two abilities. It may be that the causal coherence of the children's pretence is simply an epiphenomenon of children's general causal knowledge and counterfactual inference abilities. A more intriguing possibility, however, is that pretend play itself plays a role in the development of causal thinking and learning.

To test this idea, we need further experiments. For example, we could test whether engaging children in causal pretence improves their subsequent counterfactual reasoning. Although the extended engagement in the pretend scenarios suggests that children were indeed pretending, we could also test this more systematically by contrasting these scenarios with similar ones that did not involve pretence. We are currently investigating these issues in our laboratory, as well as looking at how and under what circumstances children generalize more complicated causal relationships.

It is worth emphasizing again that the capacities we see in causal learning and counterfactual thinking are not themselves uniquely human. Both other primates, especially great apes, and birds, especially corvids, show some ability to make causal inferences from models and to use these inferences in ecologically significant contexts, such as foraging or negotiating dominance relations [12,64,65]. Moreover, the basic structure and computations of Bayesian learning can

be found quite widely in both the visual system and the motor system [66,67]. The role of such 'forward models' in motor behaviour is especially interesting given the expansion of motor areas that accompanied the evolution of human brains, and the evolutionary value of increased motor skills [68]. Again, given the small genetic changes and rapid time scale of human evolution, it would be surprising if brand-new computations had somehow evolved, but motor system computations may have become more widely available.

The crucial difference, we argue, is in the scope and application of this sort of learning and reasoning. Human children, and the adults they become, do not restrict their counterfactual inferences to the familiar causal relations of foraging and dominance. Instead, this form of reasoning and learning extends to include the unprecedentedly wide and variable range of physical environments where humans live and the even wider range of physical and social environments that they create. Exploratory learning, causal models and counterfactual inferences are particularly helpful for dealing with this type of variability. This kind of counterfactual exploration stands in tension with the kinds of learning that may be most valuable for swift and computationally and neurally inexpensive action and decision-making, such as those involved in associative learning.

We speculate that non-human animals reserve the more computationally and neurally expensive computations involved in Bayesian learning for specific, highly ecologically valuable functions. These might include dedicated machinery for vision and motor control, or more flexible but still restricted computations that might be used in foraging, tool use or dominance negotiation. They may rely more on more computationally efficient, but less flexible and powerful learning methods such as conditioning or instrumental and trial-and-error learning to acquire broad domain-general and novel information.

Human beings can also rely on these computationally simpler types of learning, particularly under cognitive load or when responding must be swift [69]. However, the long period of human childhood gives humans the luxury of applying more powerful but more expensive types of exploratory learning to a wide range of novel information, without regard to their immediate utility.

We might compare this human strategy to the economic strategy whereby companies invest in research divisions that are not immediately profitable, but that allow for flexibility and retooling in the light of changing conditions. Investment in an extended childhood, with its many opportunities for free exploration and causal learning, may have allowed human beings to turn from simply making the same ecological widgets to developing our staggeringly wide variety of strategies for adaptive success.

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## ENDNOTE

<sup>1</sup>The full relationship between these causal models and associative models is complex and still debated [18,19]. Simple associative mechanisms may often produce representations that capture a subset of causal relations. For example, the Rescorla–Wagner rule may provide a measure of the strength of the causal relation between two stimuli [20]. Instrumental or operant conditioning may be construed as a technique for determining the causal efficacy of an agent's own actions on the world. At the other end of the spectrum, the kinds of highly complex associative mechanisms found in connectionist models may be used to implement causal models and Bayesian inferences as they may, in principle, be used to implement any other type of computation [21].

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