

# Changes in cognitive flexibility and hypothesis search across human life history from childhood to adolescence to adulthood

Alison Gopnik<sup>a,1</sup>, Shaun O'Grady<sup>a</sup>, Christopher G. Lucas<sup>b</sup>, Thomas L. Griffiths<sup>a</sup>, Adrienne Wente<sup>a</sup>, Sophie Bridgers<sup>c</sup>, Rosie Aboody<sup>d</sup>, Hoki Fung<sup>a</sup>, and Ronald E. Dahl<sup>e</sup>

<sup>a</sup>Department of Psychology, University of California, Berkeley, CA 94720; <sup>b</sup>School of Informatics, University of Edinburgh, Edinburgh EH1 2QL, United Kingdom; <sup>c</sup>Department of Psychology, Stanford University, Stanford, CA 94305; <sup>d</sup>Department of Psychology, Yale University, New Haven, CT 06520; and <sup>e</sup>School of Public Health, University of California, Berkeley, CA 94720

Edited by Andrew Whiten, University of St. Andrews, St. Andrews, United Kingdom, and accepted by Editorial Board Member Andrew G. Clark April 8, 2017 (received for review January 18, 2017)

**How was the evolution of our unique biological life history related to distinctive human developments in cognition and culture? We suggest that the extended human childhood and adolescence allows a balance between exploration and exploitation, between wider and narrower hypothesis search, and between innovation and imitation in cultural learning. In particular, different developmental periods may be associated with different learning strategies. This relation between biology and culture was probably coevolutionary and bidirectional: life-history changes allowed changes in learning, which in turn both allowed and rewarded extended life histories. In two studies, we test how easily people learn an unusual physical or social causal relation from a pattern of evidence. We track the development of this ability from early childhood through adolescence and adulthood. In the physical domain, preschoolers, counterintuitively, perform better than school-aged children, who in turn perform better than adolescents and adults. As they grow older learners are less flexible: they are less likely to adopt an initially unfamiliar hypothesis that is consistent with new evidence. Instead, learners prefer a familiar hypothesis that is less consistent with the evidence. In the social domain, both preschoolers and adolescents are actually the most flexible learners, adopting an unusual hypothesis more easily than either 6-y-olds or adults. There may be important developmental transitions in flexibility at the entry into middle childhood and in adolescence, which differ across domains.**

causal reasoning | social cognition | cognitive development | adolescence | life history

One of the most distinctive biological features of human beings is our unusual life history. Compared with our closest primate relatives, we have a dramatically extended childhood, including an exceptionally long middle childhood and adolescence. Moreover, humans have shorter interbirth intervals than our closest primate relatives, producing an even greater number of less-capable children (1). There is evidence for other human adaptations that helped cope with this flood of needy young. In contrast to our closest primate relatives, human children enjoy the benefits of care from three sources in addition to biological mothers: pair-bonded fathers (2), alloparents (3), and post-menopausal women, in particular, grandmothers (4).

It may seem evolutionarily paradoxical that humans would have developed a life history that includes such expensive and vulnerable young for such a long period. However, across many different species, including birds and both placental and marsupial mammals, there is a very general (although not perfect) correlation between relative brain size, intelligence and a reliance on learning, and an extended period of immaturity (5–7). This correlation suggests a relation between our distinctive human life history and our equally distinctive large brains and reliance on learning, particularly cultural learning. Such a relation between biology and

culture would have been coevolutionary and bidirectional: life-history changes allowed changes in cultural learning, which in turn both allowed and rewarded extended life histories. In this way, culture could have extended biology.

A number of researchers have suggested that our life history is related to our learning abilities (8–10). But what might this relation be like in more detail? It is possible that the extended human childhood and adolescence is simply a waiting period in which a large brain can grow or cultural learning can take place (11). However, both developmental psychology and neuroscience suggest that there may be more substantive differences in learning and plasticity in different developmental periods, differences that could contribute to human intelligence and culture.

We argue that there may be a developmental trade-off between cognitive abilities that allow organisms to learn the structure of a new physical or social environment, abilities that are characteristic of children, and the more adult abilities that allow skilled action on a familiar environment. Empirical evidence suggests that children may sometimes be better, and particularly more flexible, learners than adults. Ideas from the literature on developmental neuroscience, machine learning, and cultural learning may help to characterize and explain these developmental differences more precisely.

We go on to test these ideas by examining cognitive flexibility across the developmental periods of preschool, middle-childhood, adolescence, and adulthood, in both the physical and social domain.

**When Younger Learners Do Better.** Younger learners usually have more difficulty with cognitive tasks than older children and adults. Young children have characteristic deficits in executive function, working memory, attentional focus, and control (12, 13). These are precisely the same abilities required for performing complex skilled actions swiftly and effectively in adulthood. Indeed, human children are so dependent on others partly because of their deficits in these areas.

This paper results from the Arthur M. Sackler Colloquium of the National Academy of Sciences, "The Extension of Biology Through Culture," held November 16–17, 2016, at the Arnold and Mabel Beckman Center of the National Academies of Sciences and Engineering in Irvine, CA. The complete program and video recordings of most presentations are available on the NAS website at [www.nasonline.org/Extension\\_of\\_Biology\\_Through\\_Culture](http://www.nasonline.org/Extension_of_Biology_Through_Culture).

Author contributions: A.G., S.O., C.G.L., T.L.G., A.W., and R.E.D. designed research; A.G., S.O., A.W., S.B., R.A., and H.F. performed research; A.G., S.O., and C.G.L. analyzed data; and A.G. and S.O. wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission. A.W. is a guest editor invited by the Editorial Board.

<sup>1</sup>To whom correspondence should be addressed. Email: [gopnik@berkeley.edu](mailto:gopnik@berkeley.edu).

This article contains supporting information online at [www.pnas.org/lookup/suppl/doi:10.1073/pnas.1700811114/-DCSupplemental](http://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1700811114/-DCSupplemental).

However, at the same time that their executive abilities are so limited, human children learn a tremendous amount about the world easily and rapidly. They quickly and spontaneously learn about the causal structure of their physical and social environments, constructing intuitive theories of the physical, biological, and psychological world (e.g., ref. 14).

There is also empirical evidence that younger learners sometimes, counterintuitively, actually outperform older ones on learning tasks, showing more flexibility. Younger mice learn to reverse a learned rule more easily than postpubertal mice (15). Older monkeys show neural plasticity when they learn an auditory or tactile pattern, but only when the pattern is relevant to their goals; juveniles extract the patterns and demonstrate plasticity independently of goals (16). Among humans, younger learners are more able to learn new linguistic distinctions than older learners (17, 18) and they are better at imagining new uses for a tool (19). Younger children also remember information that is outside the focus of goal-directed attention better than adults and older children (20, 21).

We have recently found that preschool children also outperform older children and adults on abstract social (22) and physical (23) causal learning problems (24). In particular, younger learners are more likely to infer an initially unlikely causal hypothesis from a pattern of evidence. These kinds of causal learning are especially relevant for human evolution. Theories of the evolution of cognition stress the adaptive value of human abilities to learn both the psychological and social causal relationships that are involved in “theory of mind” and “Machiavellian intelligence,” and the physical causal relationships that underpin tool use (25, 26).

These findings suggest empirically that children might be especially flexible learners. But why would this be?

#### **Neuroscience: Trade-Offs Between Executive Function and Plasticity.**

Neuroscientists have investigated the origins of both the increased executive control and decreased plasticity that come with age. One set of developments involves synaptic changes. In the early period of development, many more new synaptic connections are made than in adulthood. With age some of these neural connections are strengthened but others are pruned, transforming a more flexible, sensitive, and plastic brain into a more effective and controlled one (27, 28).

Increasing executive control is also related to the development of prefrontal areas of the brain and their increasing connection to other brain areas. However, neuroscientists have also argued that strong frontal control has costs for exploration and learning (29). Interference with prefrontal control areas through transcranial direct current stimulation leads to a wider range of responses on a “divergent thinking” task (30), and during learning there is a characteristic release of frontal control (31).

The adolescent brain undergoes particular changes. There is significant maturational development in prefrontal areas and in areas thought to be involved in self-perception and social cognition (32), which may indicate increased plasticity. However, there is also evidence for enhanced consolidation and pruning in adolescence (33), which might suggest a period of less flexibility.

**Computation: Trade-Offs Between Exploitation and Exploration, and Narrow and Broad Search.** The trade-off between executive function and plasticity in the neuroscience literature parallels another trade-off that appears in machine learning. Reinforcement learning algorithms make an important distinction between periods of exploration, in which the system gathers information about potential actions and outcomes, and exploitation, in which information gathering is replaced by taking the actions most likely to maximize reward (34). Human life histories can be interpreted as a unique solution to the explore/exploit tension, with low executive control and high plasticity early in life maximizing exploration, and increased executive function and lower plasticity maximizing reward as we switch to exploitation.

The different strategies that learners might engage in—and their consequences for those learners—can also be characterized more precisely by considering cognitive development from the perspective of a probabilistic model approach to cognition. This approach, inspired by statistical methods that are widely used in artificial intelligence and machine learning, has become increasingly influential in cognitive science (e.g., refs. 35–40).

This approach applies particularly naturally to learning the causal structure of the environment. Probabilistic models of cognition use sophisticated causal models to specify the probability of observing a particular statistical pattern of evidence if a causal hypothesis is true (41). This makes it possible to use Bayesian inference to determine the probability that the hypothesis is true given that evidence (42). Rather than simply generating a yes or no decision about whether a particular hypothesis is true, Bayesian inference evaluates multiple hypotheses and assigns probabilities to those hypotheses (14, 35–40). Many studies have presented children with evidence patterns and alternative hypotheses that might explain those patterns, and found that children characteristically choose hypotheses that Bayesian inference suggests should be more probable (14).

However, Bayesian inference comes at a cost: the significant computational cost of evaluating hypotheses. It is impossible for any system, human or computer, to consider and compare all of the possible hypotheses relevant to a realistic learning problem. Computer scientists and statisticians often use “sampling” to help solve this problem—stochastically selecting some hypotheses rather than others—and there is evidence that people, including young children, do something similar (43–45).

The sampling process, however, presents learners with a dilemma. A learner can conduct a narrow search, only revising current hypotheses when the evidence is particularly strong and making small adjustments to accommodate new evidence. This strategy is most likely to quickly yield a “good enough” solution that will support immediate effective action. But it also means that the learner may miss a better alternative that is farther from the current hypothesis, such as a hypothesis about an unusual causal relation.

Alternatively, a learner can conduct a more exploratory search, moving to new hypotheses with only a small amount of evidence, and trying out hypotheses that are less like the current hypotheses. This strategy is less efficient if the learner’s starting hypothesis is reasonably good, and may mean that the learner wastes time considering unlikely possibilities. But it may also make the learner more likely to adopt genuinely new solutions.

There is a related contrast in the algorithms that are used in computer science. Drawing on an analogy to statistical physics, computer scientists have explored the consequences of using narrower “low-temperature” versus broader “high-temperature” searches. Continuing the analogy, “simulated annealing” (46) is one of the best ways of resolving the tension between these two strategies. Learners who begin with a broader higher-temperature search and gradually move to a narrower low-temperature search are most likely to find the optimal solution, just as in metallurgy heating a metal and then cooling it leads to the most robust structure. Moreover, as in physical cases of annealing, there may be multiple rounds of this process. We have argued for a similar developmental pattern with early broad exploratory sampling followed by a later narrower search (23, 24). Our hypothesis is that childhood and adolescence may be evolution’s way of performing simulated annealing, and hence resolving the explore/exploit trade-off.

**Cultural Learning: Trade-Offs Between Imitation and Innovation.** The causal learning problems where children do better can also be recast as cultural learning problems, and understood in relation to the cultural learning literature. Consider a learner who observes someone else performing a complicated series of actions with artifacts that produce an effect. The learner might approach this information in several ways. First, the learner might simply

reproduce the actions in detail. Alternatively, the learner might apply existing causal knowledge to the situation, and bring about the effect more directly. These two forms of learning have been the focus of the extensive “overimitation” literature, starting with the classic Horner and Whiten study (47).

Human preschoolers are sensitive to information about physical events and actor’s intentions in deciding how faithfully to imitate, and there are also developmental and cultural differences in how imitation takes place (48–52). Learners of all ages may use their existing causal and cultural knowledge to interpret the actions of another person and to decide whether and how faithfully to imitate those actions.

However, they might also use another person’s demonstration to discover a new or unexpected causal relationship. For example, consider a Pleistocene learner who sees an expert produce a flake from one side of a rock by hitting it on the other side (53), or a modern learner who watches an expert swipe to find a photo on a phone. The learner might simply imitate the demonstrator exactly. Alternatively, she might use her existing causal knowledge to bring about the result (hitting the rock at the place where she wants it to flake or using a keyboard command).

However, a learner might also use this information to infer an unexpected abstract causal principle (distant force or touch activation). She could then use this principle to design innovative actions beyond the demonstration, shaping other tools or trying other swipes for other commands. This kind of learning would both enable learners to adopt innovations in an intelligent way and to create innovations themselves.

This approach also applies to social and psychological causal learning. Imagine that a learner hears a complex narrative describing a series of human actions, again a classic cultural, as well as causal, learning scenario. The learner might simply encode the actions as they are described, recording what the actors did. She might interpret those actions in terms of an existing psychological schema. Alternatively, she might use the information in the narrative to infer new psychological or social relations.

As in the physical case, this last option might lead to both the adoption and creation of social and psychological innovations. Consider a learner who hears a story in which Sam and John live together and share a bedroom. She might interpret this story in terms of her existing cultural schemas (perhaps Sam and John are close friends with a small apartment). She might also, however, use the story to make a broader inference about the possibility of same-sex marriage.

These alternative forms of cultural learning exemplify the explore/exploit tension. The first two strategies, namely, exact imitation or reliance on causal knowledge, are likely to lead to quick and mostly effective actions. Entertaining the unlikely new causal relation is both more cognitively demanding and more risky. In the long run, however, it may confer an advantage in dealing with changing and variable environments.

Human learners of all ages may use all these strategies to some extent. However, our hypothesis is that learners at different developmental stages may be more or less likely to use different strategies. In particular, more protected and more behaviorally variable younger learners may be more likely to adopt new hypotheses than older learners. In fact, the causal learning tasks in our earlier research, in which younger learners do better than older ones, involve precisely these kinds of scenarios. Learners infer a new causal relation from a demonstration or narrative.

This developmental difference may also help resolve the tension between imitation and innovation in cultural learning (48). Human children are adept at imitation. However, the flexibility of childhood cognition may also help allow innovations to be adopted and to spread. Young children are rarely the source of complex technical innovations; actually designing and producing an effective tool, for example, is a challenging task that requires both innovation and executive skill (48, 54). However, innovations

that are effortful and rare when they first appear within a generation can become effortlessly and widely adopted by the next generation. In fact, among nonhuman animals, cultural innovations are often first produced, adopted, and spread by juveniles (55–58).

**Continuous Knowledge Acquisition vs. Discontinuous Developmental Transition.** There are two complementary mechanisms that might lead to a developmental shift from broader exploration to narrower exploitation. One is simply the accumulation of knowledge itself. As we learn more and grow more confident in our beliefs, we are less likely to change those beliefs. From a Bayesian perspective, development proceeds from a relatively “flat” prior, where different hypotheses have more similar probabilities, to a more “peaked” distribution, where some hypotheses are much more likely than others, as a learner accumulates knowledge. In Bayesian models a flatter prior would automatically lead to broader search.

Another complementary possibility, building on the literature discussed above, is that maturation and general experience lead to different degrees of plasticity and flexibility and different search strategies, independent of accumulated knowledge. There might be nonlinear changes at points of developmental transition, such as the transition from early to middle childhood at around 6 y or in adolescence, rather than a simple continuous change with accumulated knowledge.

In particular, although adolescents have more accumulated experience than younger children, there is evidence, as noted above, that adolescence may also be a period of enhanced plasticity and learning (59, 60), especially for social domains (32, 61), in part through the privileging of social information processing and the salience of social rewards in decision making (62, 63). Cultural innovations, such as new socially significant forms of language, dress, or music often first appear in adolescents. Adolescence might be an extra round of annealing in the social sphere. However, there is also evidence that adolescence may be a period of pruning and consolidation.

In fact, two contrasting developmental patterns characterize adolescence (64, 65). On some measures, such as cognitive control, and self-regulation, there is a relatively linear trajectory from childhood through adolescence to adulthood. On others, such as sensation-seeking and risk-taking, both forms of exploration, there is a marked increase associated with the onset of puberty, and an inverted U pattern peaking in adolescence and then declining. There is extensive research on risk-taking and decision-making in adolescence but, to our knowledge, no research on causal learning.

**Current Studies.** We approach these questions by extending two earlier causal learning experiments. Where the original experiments contrasted preschoolers with either 6-y-old children or adults, we report results covering the entire developmental span from preschool to adulthood, with special focus on the transition to middle childhood and adolescence, periods not explored previously. This approach allows us to explore learning across human life history, and to ask whether there are distinctive developmental transitions.

Both experiments have the same logic. We contrast two hypotheses about how objects or people work: one that is initially more likely, at least for adults, and one that is more unusual. In Exp. 1 we contrast the hypothesis that individual objects activate a machine with the hypothesis that particular combinations of objects do. In Exp. 2 we contrast the hypothesis that someone took a risk because of their personal traits with the hypothesis that they took the risk because of the situation they encountered.

In one condition, participants receive covariation evidence that supports the likely hypothesis. In a second, otherwise identical condition, they receive covariation evidence that supports the unlikely hypothesis. In a third baseline condition, participants do not receive evidence either way. We record whether participants of different ages adopt the likely or unlikely hypothesis in each condition.



The different conditions allow us to control for alternative factors that might influence performance on these tasks. In the first two conditions, supporting the likely hypothesis or the unlikely one, the participants see similar agents perform similar actions on similar objects; all that differs is the covariation between causes and effects. Moreover, both conditions require that the learner attend to and use the particular pattern of data presented in the demonstration. Whether they adopt the likely or unlikely hypothesis, the learner still has to attend to the specific details of the evidence to answer correctly. Differences in performance, then, should reflect differences in causal learning rather than more general information-processing, linguistic, or motivational factors.

### Exp. 1: Reasoning About the Causes of Physical Events

In an earlier study, Lucas et al. (23) found that, across three different experiments, with different participants and designs, preschool children learned an unusual abstract physical causal relationship but adults had difficulty.

In the second experiment of that study, preschool children and adults were presented with a machine that lights up when you place certain patterns of blocks on top, and were told that “blicketness” makes the machine go. First, in a training trial, participants saw unambiguous covariation evidence suggesting that the machine operated according to a general logical rule. In one condition, the machine operated on a disjunctive “or” rule: each block either activated the machine or did not. Accounts of adult causal reasoning suggest that this disjunctive rule is the default assumption for adults (e.g., ref. 66). In the other condition, the machine operated on a more unusual conjunctive “and” rule: two blocks had to be placed on the machine at the same time to make it activate. Four-year-old children and adults in both conditions then saw an ambiguous test trial with new blocks that was consistent with either general principle. In a baseline condition, participants only saw the ambiguous trial without the training trials. In each condition, participants were then asked whether each block was or was not a “blicket” and were asked to activate the machine.

Children learned the appropriate general rule in each condition and applied it to the ambiguous case. Adults applied the default disjunctive rule in the ambiguous case even when the earlier evidence weighed against it.

In Exp. 1 we used exactly the same methods across the entire developmental range, including 6- to 7-y-olds, 9- to 11-y-olds, and 12- to 14-y-olds. Fig. 1 provides a visual display of the pattern of evidence used for training and test trials.

We extended the contrast between preschoolers and adults to include school-aged children and adolescents. This approach

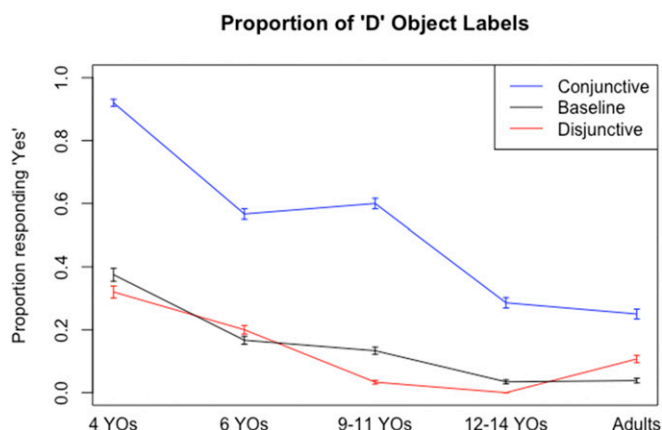


Fig. 2. Proportion of participants labeling test objects as “blickets” with SEs.

allowed us to examine the transitions from early to middle childhood, from middle childhood to adolescence, and from adolescence to adulthood. Would there be differences between preschoolers and school-age children? Would adolescents be less flexible and more like adults? Or might they be more flexible than school-aged children and adults with the inverted U pattern? Finally, would there be a continuous change as children accumulated more knowledge or more discontinuous changes at developmental transitions?

### Results.

**Blicket judgments.** We combined new data collected from younger school-aged children (6- to 7-y-olds), older preadolescent children (9- to 11-y-olds), and young adolescents (12- to 14-y-olds) with the data from 4-y-olds and adults tested with the identical method in Lucas et al. (23).

If the observers believe the machine operates on an unusual conjunctive rule, requiring multiple blickets to operate, they should say that F, D, and possibly E are blickets and use multiple objects to make the machine go. If observers believe that the machine works on the “disjunctive” rule, in contrast, they should say that F is a blicket but that D and E are not and put single objects on the machine. [The evidence that E is a blicket is less strong than the evidence for D, so participants should be less likely to say that E is a blicket than D (23).] (See *SI Appendix, Table S5* for analysis of E judgments, consistent with these predictions.)

Fisher’s exact tests revealed no significant differences between conditions or ages for the unambiguous F object; as predicted all of the age groups in all of the conditions said that F was a blicket (means ranged from 0.7 to 0.96).

Fig. 2 presents the proportion of participants in each age group labeling the critical D test object as a blicket by condition. Because the dependent measure is a binary response, we used comparisons of generalized linear models to identify the statistical model with the best fit to the data. Results of model comparisons can be found in *SI Appendix, Table S4*.

A model predicting the binary D judgment from condition and age group with no interactions was best fit to the data. Post hoc tests using Tukey’s honest significant differences (HSD) for D object judgments revealed a significant difference between the conjunctive ( $M = 0.52$ ,  $SE = 0.02$ ) and the disjunctive ( $M = 0.13$ ,  $SE = 0.01$ ;  $t = -0.391$ ,  $P < 0.001$ ) and baseline ( $M = 0.15$ ,  $SE = 0.01$ ;  $t = -0.374$ ,  $P < 0.001$ ) conditions, and there was no significant difference between the disjunctive and baseline conditions ( $t = -0.017$ ,  $P = 0.923$ ).

In addition to the model comparisons, we conducted planned comparisons for the theoretically crucial developmental contrasts in the critical conjunctive condition, using Fisher’s exact

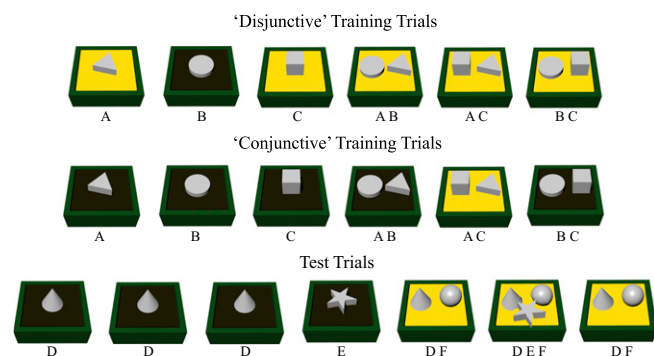


Fig. 1. Schematic of the procedure for Exp. 1. The yellow rectangle represents the machine’s activation. “Disjunctive” training provides evidence of the more common, disjunctive hypothesis. “Conjunctive” training provides support for the less common conjunctive hypothesis. “Test” trials presented ambiguous evidence about the “D” object.



the model comparisons can be found in *SI Appendix, Table S12*. Fig. 4 plots the average situation attribution score for each age group by condition.

As in Exp. 1, we also performed planned comparisons for the crucial age transitions in the situation condition, using *t* tests. The critical situation condition revealed whether participants would adopt the unlikely situation hypothesis given evidence, or would instead attribute actions to traits as they did in the person and baseline conditions.

In the Seiver et al. (22) data the 6-y-olds, but not the 4-y-olds, showed a trait bias in the situation condition, suggesting a transition at school age. In this experiment, we also tested the adolescent transition by comparing the 12- to 14-y-olds to 6- and 9-y-olds and to adults. The adolescents showed an interesting pattern, unlike the pattern in Exp. 1, which appeared to be responsible for the interaction effect in the model. Adolescent responses in the situation condition differed both from adults and younger children in an inverted U pattern. In the situation condition 12- to 14-y-olds ( $t = -4.1048$ ,  $P < 0.001$ ) made more situation attributions than adults, and 12- to 14-y-olds also made significantly more situation attributions than 6-y-olds ( $t = -2.34$ ,  $P = 0.02$ ), although they were not significantly different from 9- to 11-y-olds.

We also performed additional analyses using Tukey's HSD test. Participants in both the person ( $M = 0.2$ ,  $SE = 0.02$ ;  $t = -0.531$ ,  $P < 0.001$ ) and baseline ( $M = 0.49$ ,  $SE = 0.03$ ;  $t = -0.531$ ,  $P < 0.001$ ) conditions provided significantly fewer situation attributions than those in the situation ( $M = 1.02$ ,  $SE = 0.03$ ) condition. There was not a significant difference between the baseline and person conditions, suggesting a trait bias.

Given the interaction, we also used Tukey's HSD tests to examine age differences separately for each condition. There were no significant age differences in attribution scores in the person condition; all age groups produced trait explanations when these explanations were congruent with the data, and rarely made situation attributions.

The baseline condition allowed us to assess participants' judgments when no evidence was available (their "prior" in Bayesian terms). Post hoc Tukey tests revealed that 4-y-olds ( $M = 0.93$ ,  $SE = 0.08$ ) provided significantly more situation attributions than both 12- to 14-y-olds ( $M = 0.24$ ,  $SE = 0.06$ ;  $t = -0.694$ ,  $P = 0.001$ ) and adults ( $M = 0.38$ ,  $SE = 0.05$ ;  $t = -0.55$ ,  $P = 0.004$ ). Although both 6-y-olds ( $M = 0.43$ ,  $SE = 0.1$ ;  $t = -0.49$ ,  $P = 0.09$ ) and 9- to 11-y-olds ( $M = 0.55$ ,  $SE = 0.11$ ;  $t = -0.386$ ,  $P = 0.49$ ) provided fewer situation attributions than 4-y-olds, these differences did not reach statistical significance. This finding suggested that a trait bias developed around 6 y and was maintained with age.

**Discussion.** In the person condition, participants of all ages mostly made trait attribution explanations, in accordance with the evidence. In the baseline condition, with no evidence, there was a decrease in situation explanations with age. Accumulating experience may have led to a trait bias.

In the situation condition, in which the learners had to infer the unusual hypothesis, there was an interesting developmental reversal, with an inverse U pattern. Twelve- to 14-y-olds were less likely to make trait attributions than either 6-y-olds or adults. In other words, although the adolescents had developed a strong bias to begin with, they overcame that bias when they received contradictory evidence. The adolescents showed the largest gap between the baseline condition and the situation condition.

These findings support the idea that adolescents may be particularly interested in discovering new social possibilities. This finding is consistent with the fact that, compared with adults, adolescents show greater activation in brain regions associated with self-perception and social cognition (71, 72), and that adolescents are often at the forefront of social change.

Average Situation Attribution Score

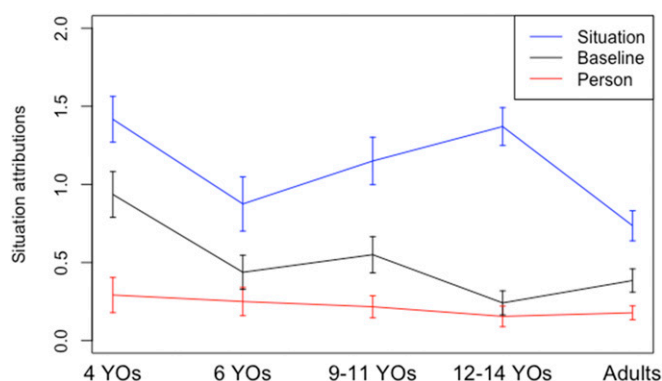


Fig. 4. Average attribution scores by age group and condition with SEs. YO, year old.

Finally, these results suggest that changes in flexibility are not solely because of the accumulation of knowledge. The adolescents should have accumulated more knowledge than the younger children and this was reflected in their trait bias in the baseline condition. However, the adolescents were also the most flexible social thinkers; they were most able to overcome prior biases in the face of new evidence.

## General Discussion and Conclusions

These results support the suggestion that the extended human period of immaturity allows a period of flexible hypothesis search in cultural learning. In both studies, we also found some evidence for developmental transitions, particularly from early to middle childhood and at adolescence.

The crucial conditions involved cases where the evidence and the existing hypotheses were in conflict, the conjunctive condition in Exp. 1 and the situation condition in Exp. 2. In both studies 4-y-olds and 6- to 7-y-olds were significantly different in these conditions. In both studies, however, we did not see significant differences between 6- to 7-y-olds and 9- to 11-y-olds.

Similarly, we found evidence for a transition in adolescence in both studies in these conditions, but this transition went in opposite directions. In the physical case, in the conjunctive condition adolescents were similar to adults but less flexible than either 6-y-olds or 9- to 11-y-olds. Like adults, the adolescents seemed reluctant to revise physical knowledge they had already acquired. In the social case, however, in the situation condition adolescents were more flexible than either 6-y-olds or adults. This finding is consistent with the idea that adolescents are more tuned to the social domain than the physical one, and are willing to entertain new social possibilities.

These findings also raise the question of the interaction between biological and environmental factors in the unfolding of life history. The findings in the baseline conditions suggest that children are gradually accumulating more knowledge and that this may play a role in the decline of cognitive flexibility.

However, the discontinuous pattern in the conjunctive and situation conditions suggests that other factors also play a role. Biological changes like puberty may play a role in the adolescent transitions. There may also be more complex interactions between the changing life experiences that come with different developmental stages and hypothesis search and flexibility. Adolescence is not only a time of biological change; it is also a time of new social motivation and experience. Similarly, there is a complex interaction between biological changes at around 6 y



and experiences such as school in our culture, or more informal apprenticeships in cultures without formal schooling.

It is also plausible that a playful protected environment may lead to more flexible, exploratory and childlike learning, even in adulthood, and that even in childhood, stressful or resource-poor environments may lead to less flexibility and a more adult-like emphasis on exploitation (see, e.g., refs. 73 and 74).

These issues are all worthy of exploration, as are extensions of these studies to new domains. The physical causal learning results in Exp. 1 have been replicated in low socioeconomic status preschoolers in Peru and the United States,\* but more extensive cross-cultural comparisons, including the social tasks and extending to forager and small-scale agricultural cultures, would also be important. The current findings do, however, suggest a relation between biology and culture, in particular between the distinctive childhood and adolescence of our life history and our equally distinctive ability to learn about and create new social and physical environments.

## Methods

Data from the new participants in this study can be found on the Open Science Framework (<https://osf.io>) under the profile for Shaun O'Grady.

### Exp. 1.

**Participants.** Children aged 6- to 7-y-old, ( $n = 90$ ), 9- to 11-y-old ( $n = 90$ ), and 12- to 14-y-old ( $n = 86$ ) participated. We combined these new data with that reported for preschoolers and adults in Exp. 2 of Lucas et al. (23) to compare performance from preschool to adulthood. For all participants in both experiments reported here, parents provided written informed consent and the child participants provided either written assent (9- to 14-y-olds) or verbal assent (4- to 7-y-olds) in accordance with protocols approved by the University of California, Berkeley Committee for the Protection of Human Subjects.

**Procedure.** Participants from each age group were randomly assigned to one of three conditions: two training conditions (conjunctive and disjunctive conditions) and a third condition with no training, termed the baseline condition. In each condition the participants were shown nine different blocks (A, B, C, A<sub>2</sub>, B<sub>2</sub>, C<sub>2</sub>, D, E, and F). Participants were presented with a machine and were informed that "blicketness" makes the machine light up and play music.

In both of the training conditions, the experimenter placed individual blocks or combinations of blocks on the machine in the same order (Fig. 1). In the conjunctive condition the machine only activated when the experimenter placed both A and C on the machine at the same time, providing evidence that supports a conjunctive rule about the machine's operation. In the disjunctive condition the machine activated any time either A or C were placed on the machine, suggesting that only one of the two blocks was needed. After the two training trials participants saw one test trial with three new items: D, E, and F. The test trials provided ambiguous information that could support either the conjunctive or disjunctive rule (i.e., D and F are both blickets or just F is a blicket). In the baseline condition, participants were not given any prior training about the rule

for operating the machine, but instead were presented with two ambiguous test trials. We recorded results from the second test trial but there were no significant differences between them.

The three conditions only differed in the covariation between the blocks and the machine. In all three conditions, at the end of both training and test trials, the experimenter pointed to each item individually and asked the participant if that item was a blicket or not a blicket. Finally, the experimenter then gestured to the set of three objects and asked the participant, "Which of these [gesturing to the three test objects] would you use to turn on the machine?"

### Exp. 2.

**Participants.** The same 9- to 11-y-olds ( $n = 90$ ) and 12- to 14-y-olds ( $n = 86$ ) in Exp. 1 also participated in this experiment. Order of administration of the tasks was counterbalanced to avoid interference; there were no order effects. An additional 240 adult participants were recruited for an online version of this experiment via Amazon's Mechanical Turk. We combined these data with the original data from Seiver et al. (22) for 4- and 6-y-olds.

**Procedure and coding.** Participants were randomly assigned to one of three conditions in which two dolls interacted with two toys. Subjects assigned to the situation condition saw two dolls play on one toy four times and then saw those same dolls avoid playing on a second toy four times. This pattern of covariation should suggest that something about the situation caused the pattern of actions (i.e., "her friend played on the bicycle" or "the trampoline is dangerous"). Those assigned to the person condition saw one doll play on both toys four times, whereas the other doll avoided playing on both toys four times. This evidence should suggest that the actions resulted from an inherent trait of the doll, and produce trait-based explanations, such as "she's the type of doll that gets scared/is brave" or "she knows how to ride a bike." Finally, in a baseline condition, participants saw one doll play on one toy four times, whereas the other doll avoided the other toy four times. Participants in this condition could not rely on covariation information to make attributions because they had not seen how each doll acted on the other toy. After they watched the dolls interact with the toys, each participant was asked why each doll either played or did not play on the second toy.

Explanations referring to an enduring characteristic of the doll were coded as "person" attributions and were given a score of 0 (e.g., "Because she might be more brave than the other one"). When an explanation referenced an aspect of the toy or situation, the response was coded as a "situation" attribution and given a score of 1 (e.g., "The trampoline doesn't have any edges"). Some explanations referred to both personal traits and situational factors and were coded as "interactions" and given a score of 0.5. See *SI Appendix, Table S9* for a list of example responses by category. Reliability coding was conducted on 16% of the responses by a second coder who was blind to condition, and interrater reliability was high (Cohen's  $\kappa = 0.967$ ,  $P < 0.001$ ). Coded explanation responses for each participant were summed to provide a "situation" attribution score for each participant.

**Analyses.** All analyses in both experiments were performed using the R statistical programming language (75). Preliminary analyses revealed no effect of block shape, doll name, toy, or the order in which the dolls played. Linear regression models found no effect of gender of the participants or the experimenter in either experiment (see *SI Appendix, Tables S3 and S11*).

**ACKNOWLEDGMENTS.** This work was funded by the National Science Foundation Graduate Research Fellowship under Grant DGE 1106400 (to S.O.); National Science Foundation Grant BCS-331620 (to A.G. and T.L.G.); and grants from the Bezos Foundation and McDonnell Foundation (to A.G.).

\*Wente AO, et al., Cognitive Development Society Meeting, October 9–11, 2015, Columbus, OH.

- Hill K, Kaplan H (1999) Life history traits in humans: Theory and empirical studies. *Annu Rev Anthropol* 28:397–430.
- Chapais B (2009) *Primeval Kinship: How Pair-Bonding Gave Birth to Human Society* (Harvard Univ Press, Cambridge, MA).
- Hrdy SB (2011) *Mothers and Others* (Harvard Univ Press, Cambridge, MA).
- Hawkes K, O'Connell JF, Jones NG, Alvarez H, Charnov EL (1998) Grandmothering, menopause, and the evolution of human life histories. *Proc Natl Acad Sci USA* 95:1336–1339.
- Bennett PM, Harvey PH (1985) Brain size, development and metabolism in birds and mammals. *J Zool* 207:491–509.
- Weisbecker V, Goswami A (2010) Brain size, life history, and metabolism at the marsupial/placental dichotomy. *Proc Natl Acad Sci USA* 107:16216–16221.
- Street SE, Navarrete AF, Reader SM, Laland KN (2017) Coevolution of cultural intelligence, extended life history, sociality, and brain size in primates. *Proc Natl Acad Sci USA* 114:7908–7914.
- Bruner JS (1972) Nature and uses of immaturity. *Am Psychol* 27:687–708.
- Konner M (2010) *The Evolution of Childhood: Relationships, Emotion, Mind* (Harvard Univ Press, Cambridge, MA).
- Bjorklund DF, Green BL (1992) The adaptive nature of cognitive immaturity. *Am Psychol* 47:46–54.
- Bogin BA, Smith BH (1996) Evolution of the human life cycle. *Am J Hum Biol* 8:703–716.
- Munakata Y, Casey BJ, Diamond A (2004) Developmental cognitive neuroscience: Progress and potential. *Trends Cogn Sci* 8:122–128.
- Carlson SM (2005) Developmentally sensitive measures of executive function in preschool children. *Dev Neuropsychol* 28:595–616.
- Gopnik A, Wellman HM (2012) Reconstructing constructivism: Causal models, Bayesian learning mechanisms, and the theory theory. *Psychol Bull* 138:1085–1108.
- Johnson C, Wilbrecht L (2011) Juvenile mice show greater flexibility in multiple choice reversal learning than adults. *Dev Cogn Neurosci* 1:540–551.
- Buonomano DV, Merzenich MM (1998) Cortical plasticity: From synapses to maps. *Annu Rev Neurosci* 21:149–186.
- Werker JF, Hensch TK (2015) Critical periods in speech perception: New directions. *Annu Rev Psych* 66:173–196.
- Kuhl PK (2004) Early language acquisition: Cracking the speech code. *Nat Rev Neurosci* 5:831–843.

19. German TP, Defeyter MA (2000) Immunity to functional fixedness in young children. *Psychon Bull Rev* 7:707–712.
20. Plebanek DJ, Sloutsky VM (April 1, 2017) Costs of selective attention: When children notice what adults miss. *Psychol Sci*, 10.1177/0956797617693005.
21. Sloutsky VM, Fisher AV (2004) When development and learning decrease memory. Evidence against category-based induction in children. *Psychol Sci* 15: 553–558.
22. Seiver E, Gopnik A, Goodman ND (2013) Did she jump because she was the big sister or because the trampoline was safe? Causal inference and the development of social attribution. *Child Dev* 84:443–454.
23. Lucas CG, Bridgers S, Griffiths TL, Gopnik A (2014) When children are better (or at least more open-minded) learners than adults: Developmental differences in learning the forms of causal relationships. *Cognition* 131:284–299.
24. Gopnik A, Griffiths TL, Lucas CG (2015) When younger learners can be better (or at least more open-minded) than older ones. *Curr Dir Psychol Sci* 24:87–92.
25. Byrne RW (1995) *The Thinking Ape: Evolutionary Origins of Intelligence* (Oxford Univ Press, Oxford).
26. Byrne R, Whiten A (1989) *Machiavellian Intelligence: Social Expertise and the Evolution of Intellect in Monkeys, Apes, and Humans* (Oxford Univ Press, Oxford).
27. Huttenlocher PR (1990) Morphometric study of human cerebral cortex development. *Neuropsychologia* 28:517–527.
28. Huttenlocher PR (2009) *Neural Plasticity* (Harvard Univ Press, Cambridge, MA).
29. Thompson-Schill SL, Ramscar M, Chrysikou EG (2009) Cognition without control: When a little frontal lobe goes a long way. *Curr Dir Psychol Sci* 18:259–263.
30. Chrysikou EG, et al. (2013) Noninvasive transcranial direct current stimulation over the left prefrontal cortex facilitates cognitive flexibility in tool use. *Cogn Neurosci* 4: 81–89.
31. Bassett DS, et al. (2011) Dynamic reconfiguration of human brain networks during learning. *Proc Natl Acad Sci USA* 108:7641–7646.
32. Blakemore SJ, Choudhury S (2006) Development of the adolescent brain: Implications for executive function and social cognition. *J Child Psychol Psychiatry* 47:296–312.
33. Lebel C, Beaulieu C (2011) Longitudinal development of human brain wiring continues from childhood into adulthood. *J Neurosci* 31:10937–10947.
34. Kaelbling LP, Littman ML, Moore AW (1996) Reinforcement learning: A survey. *J Art Int Res* 4:237–285.
35. Gopnik A, et al. (2004) A theory of causal learning in children: Causal maps and Bayes nets. *Psychol Rev* 111:3–32.
36. Perfors A, Tenenbaum JB, Griffiths TL, Xu F (2011) A tutorial introduction to Bayesian models of cognitive development. *Cognition* 120:302–321.
37. Tenenbaum JB, Kemp C, Griffiths TL, Goodman ND (2011) How to grow a mind: Statistics, structure, and abstraction. *Science* 331:1279–1285.
38. Gopnik A (2012) Scientific thinking in young children: Theoretical advances, empirical research, and policy implications. *Science* 337:1623–1627.
39. Xu F, Kushnir T (2013) Infants are rational constructivist learners. *Curr Dir Psychol Sci* 22:28–32.
40. Kushnir T, Xu F, eds (2012) *Rational Constructivism in Cognitive Development* (Academic, Cambridge, MA), Vol 43.
41. Pearl J (2009) *Causality* (Cambridge Univ Press, Cambridge, UK), 2nd Ed.
42. Griffiths TL, Chater N, Kemp C, Perfors A, Tenenbaum JB (2010) Probabilistic models of cognition: Exploring representations and inductive biases. *Trends Cogn Sci* 14: 357–364.
43. Bonawitz E, Denison S, Griffiths TL, Gopnik A (2014) Probabilistic models, learning algorithms, and response variability: Sampling in cognitive development. *Trends Cogn Sci* 18:497–500.
44. Denison S, Bonawitz E, Gopnik A, Griffiths TL (2013) Rational variability in children's causal inferences: The sampling hypothesis. *Cognition* 126:285–300.
45. Bonawitz E, Denison S, Gopnik A, Griffiths TL (2014) Win-stay, lose-sample: A simple sequential algorithm for approximating Bayesian inference. *Cognit Psychol* 74:35–65.
46. Kirkpatrick S, Gelatt CD, Jr, Vecchi MP (1983) Optimization by simulated annealing. *Science* 220:671–680.
47. Horner V, Whiten A (2005) Causal knowledge and imitation/emulation switching in chimpanzees (*Pan troglodytes*) and children (*Homo sapiens*). *Anim Cogn* 8:164–181.
48. Legare CH, Nielsen M (2015) Imitation and innovation: The dual engines of cultural learning. *Trends Cogn Sci* 19:688–699.
49. Williamson RA, Meltzoff AN (2011) Own and others' prior experiences influence children's imitation of causal acts. *Cogn Dev* 26:260–268.
50. Buchsbaum D, Gopnik A, Griffiths TL, Shafto P (2011) Children's imitation of causal action sequences is influenced by statistical and pedagogical evidence. *Cognition* 120: 331–340.
51. Berl RE, Hewlett BS (2015) Cultural variation in the use of overimitation by the Aka and Ngandu of the Congo Basin. *PLoS One* 10:e0120180.
52. Legare CH (2017) Cumulative cultural learning: Development and diversity. *Proc Natl Acad Sci USA* 114:7877–7883.
53. Morgan TJH, et al. (2015) Experimental evidence for the co-evolution of hominin tool-making teaching and language. *Nat Commun* 6:6029.
54. Beck SR, Apperly IA, Chappell J, Guthrie C, Cutting N (2011) Making tools isn't child's play. *Cognition* 119:301–306.
55. Aplin LM, et al. (2015) Experimentally induced innovations lead to persistent culture via conformity in wild birds. *Nature* 518:538–541.
56. Kawamura S (1959) The process of sub-culture propagation among Japanese macaques. *Primates* 2:43–60.
57. Aplin LM, Sheldon BC, McElreath R (2017) Conformity does not perpetuate sub-optimal traditions in a wild population of songbirds. *Proc Natl Acad Sci USA* 114: 7830–7837.
58. Perry SE, Barrett BJ, Godoy I (2017) Older, sociable capuchins (*Cebus capucinus*) invent more social behaviors, but younger monkeys innovate more in other contexts. *Proc Natl Acad Sci USA* 114:7806–7813.
59. Crone EA, Dahl RE (2012) Understanding adolescence as a period of social-affective engagement and goal flexibility. *Nat Rev Neurosci* 13:636–650.
60. Piekarski DJ, et al. (2017) Does puberty mark a transition in sensitive periods for plasticity in the associative neocortex? *Brain Res* 1654:123–144.
61. Blakemore SJ, Mills KL (2014) Is adolescence a sensitive period for sociocultural processing? *Annu Rev Psychol* 65:187–207.
62. Cardoos SL, et al. (2017) Social status strategy in early adolescent girls: Testosterone and value-based decision making. *Psychoneuroendocrinology* 81:14–21.
63. Braams BR, Peters S, Peper JS, Güroğlu B, Crone EA (2014) Gambling for self, friends, and antagonists: Differential contributions of affective and social brain regions on adolescent reward processing. *Neuroimage* 100:281–289.
64. Braams BR, van Duijvenvoorde ACK, Peper JS, Crone EA (2015) Longitudinal changes in adolescent risk-taking: A comprehensive study of neural responses to rewards, pubertal development, and risk-taking behavior. *J Neurosci* 35:7226–7238.
65. Steinberg L, et al. (2017) Around the world, adolescence is a time of heightened sensation seeking and immature self-regulation. *Dev Sci*, 10.1111/desc.12532.
66. Cheng PW (1997) From covariation to causation: A causal power theory. *Psychol Rev* 104:367–405.
67. Kelley HH (1967) Attribution theory in social psychology. *Nebraska Symposium on Motivation* 15:192–238.
68. Jones EE, Harris VA (1967) The attribution of attitudes. *J Exp Soc Psychol* 3:1–24.
69. Horhota M, Blanchard-Fields F (2006) Do beliefs and attributional complexity influence age differences in the correspondence bias? *Soc Cogn* 24:310–337.
70. Morris MW, Nisbett RE, Peng K (1995) Causal attribution across domains and cultures. *Causal Cognition: A Multidisciplinary Debate*, eds Sperber D, Premack D, Premack AJ (Clarendon Press, Oxford), pp 577–612.
71. Pfeifer JH, et al. (2009) Neural correlates of direct and reflected self-appraisals in adolescents and adults: When social perspective-taking informs self-perception. *Child Dev* 80:1016–1038.
72. Pfeifer JH, Lieberman MD, Dapretto M (2007) "I know you are but what am I?": Neural bases of self- and social knowledge retrieval in children and adults. *J Cogn Neurosci* 19:1323–1337.
73. Gee DG, et al. (2013) Early developmental emergence of human amygdala-prefrontal connectivity after maternal deprivation. *Proc Natl Acad Sci USA* 110:15638–15643.
74. Nettle D, Frankenhuys WE, Rickard IJ (2013) The evolution of predictive adaptive responses in human life history. *Proc Biol Sci*, 10.1098/rspb.2013.1343.
75. R Core Team (2012) R: A language and environment for statistical computing. (R Foundation for Statistical Computing, Vienna).