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Causal Information-Seeking Strategies Change Across Childhood and Adolescence

Kate Nussenbaum,[a] Alexandra O. Cohen,[a] Zachary J. Davis,[a] David J. Halpern,[a] Todd M. Gureckis,[a,b,c] Catherine A. Hartley[a,b]

[a]*Department of Psychology, New York University*
[b]*Center for Neural Science, New York University*
[c]*Center for Data Science, New York University*

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Abstract

Intervening on causal systems can illuminate their underlying structures. Past work has shown that, relative to adults, young children often make intervention decisions that appear to confirm a single hypothesis rather than those that optimally discriminate alternative hypotheses. Here, we investigated how the ability to make informative causal interventions changes across development. Ninety participants between the ages of 7 and 25 completed 40 different puzzles in which they had to intervene on various causal systems to determine their underlying structures. Each puzzle comprised a three- or four-node computer chip with hidden wires. On each trial, participants viewed two possible arrangements of the chip's hidden wires and had to select a single node to activate. After observing the outcome of their intervention, participants selected a wire configuration and rated their confidence in their selection. We characterized participant choices with a Bayesian measurement model that indexed the extent to which participants selected nodes that would best disambiguate the two possible causal structures versus those that had high causal centrality in one of the two causal hypotheses but did not necessarily discriminate between them. Our model estimates revealed that the use of a discriminatory strategy increased through early adolescence. Further, developmental improvements in intervention strategy were related to changes in the ability to accurately judge the strength of evidence that interventions revealed, as indexed by participants' confidence in their selections. Our results suggest that improvements in causal information-seeking extend into adolescence and may be driven by metacognitive sensitivity to the efficacy of previous interventions in discriminating competing ideas.

Keywords: Cognitive development; Causal learning; Causal interventions; Decision-making; Adolescence; Bayesian modeling

Correspondence should be sent to Catherine A. Hartley, Department of Psychology, New York University, 6 Washington Place, New York, NY 10003. E-mail: cate@nyu.edu

Kate Nussenbaum and Alexandra O. Cohen shared first authorship.

1. Introduction

We frequently manipulate the causal systems that make up our environments. We take medicine when we feel sick; we plug our phones in when they won't turn on; we water our plants when they begin to wilt. While these actions take advantage of our causal knowledge, they also often reveal information that can help us refine our understanding of causal relations (Pearl, 2009; Sloman & Lagnado, 2005; Steyvers, Tenenbaum, Wagenmakers, & Blum, 2003). Critically, the actions we take to intervene on causal systems vary in how informative they are (Bramley, Dayan, Griffiths, & Lagnado, 2017; Coenen, Rehder, & Gureckis, 2015; Tong & Koller, 2001); some actions are more likely to elicit evidence that can distinguish competing hypotheses about causal relations, leading to increased knowledge of the structure of causal systems.

Imagine, for example, a teenager first learning how to drive and maintain a car. She may believe that the car can run smoothly only when filled with premium gas. She may intervene to confirm this hypothesis by filling her tank with the most expensive gas offered at the nearby station. If her car were to run smoothly, she may take this as evidence confirming her initial hypothesis. However, if she were to consider a competing hypothesis—that the car can run well on either premium gas or regular gas—she may instead fill her tank with the cheaper, regular gas. If her car were to sputter and stop, she would gain evidence in favor of her first hypothesis, but if it were to drive without issues, she would gain evidence in favor of the second. She could then exploit this knowledge the next time she has to fill her gas tank and forego the more expensive option. In this way, different interventions bring about different sets of evidence that vary in the extent to which they can discriminate competing ideas.

Selecting interventions that can disentangle competing ideas may be particularly useful for children and adolescents, whose relative inexperience across different physical and social domains may impose fewer constraints on their causal hypotheses (Gopnik et al., 2017). Rather than characterizing change across a broad age range, studies examining the development of causal learning have primarily focused on young children. This work has shown that children can derive sophisticated causal knowledge about the structure of their environments through making causal interventions during play (Cook, Goodman, & Schulz, 2011; Gopnik, 2012; Kushnir & Gopnik, 2005; Schulz & Bonawitz, 2007; Schulz, Gopnik, & Glymour, 2007; Sobel & Sommerville, 2010). However, while young children can make informative interventions that allow them to disambiguate different underlying causal structures (Cook et al., 2011; McCormack, Bramley, Frosch, Patrick, & Lagnado, 2016; Sobel & Sommerville, 2010), in more complex task contexts, they often select suboptimal interventions that cannot discriminate between competing hypotheses (Kuhn et al., 1995; Kuhn & Phelps, 1982; Meng, Bramley, & Xu, 2018; Rieber, 1969). Thus, while children actively explore causal systems to support their own learning, they may do so suboptimally, often making interventions that do not enable them to gain discriminatory information that can facilitate understanding of causal systems.

Evidence suggests that adults perform more informative causal interventions than children, though few studies have tested children and adults within the same experiment with identical materials. Adults often choose highly informative interventions in more complex node-selection tasks with probabilistic links (Bramley, Lagnado, & Speekenbrink, 2015; Steyvers et al., 2003), while children often choose uninformative interventions even in simple experiments with deterministic intervention outcomes (Meng et al., 2018). Studies of scientific hypothesis testing in which children and adults have participated in the same task further support the idea that adults are better active causal learners than children—adults designed more systematic and informative tests of their scientific hypotheses, relative to children in third, fifth, and sixth grades (Klahr, Fay, & Dunbar, 1993; Schauble, 1996). Taken together, prior work indicates that causal information-seeking strategies change from early childhood to early adulthood, but, to our knowledge, no studies have examined how active exploration of causal systems changes continuously across adolescence. The goal of the current investigation is to address this gap in the literature, by examining how causal intervention strategies shift throughout this understudied developmental period.

Selecting interventions that maximize information gain may require multiple cognitive mechanisms that continue to develop throughout late childhood and adolescence. When faced with intervention decisions, individuals must prospectively imagine the outcomes of different actions (Sloman & Lagnado, 2005). They must then evaluate whether these outcomes provide evidence for one causal hypothesis over another to guide action selection (Coenen & Gureckis, 2015). Previous research suggests that each of these component mechanisms may undergo marked change throughout adolescence. For example, individuals' use of mental models of the environment to prospectively compare the outcomes of different decisions increases through the teenage years (Decker, Otto, Daw, & Hartley, 2016). Additionally, the ability to implement proactive cognitive control processes to suppress prepotent responses in favor of planned, goal-directed actions continues to improve throughout late childhood and adolescence (Chatham, Frank, & Munakata, 2009; Munakata, Snyder, & Chatham, 2013; Raab & Hartley, 2018). Beyond the use of mental models of action outcomes to guide decision-making, the ability to evaluate the extent to which different observations support causal hypotheses may also undergo marked improvement across adolescence (Gopnik et al., 2017). Though few studies have examined causal inference in adolescence, one study (Gopnik et al., 2017) found that young adolescents actually outperformed adults in some contexts, perhaps due to increased flexibility in responding to new evidence that contradicted their prior beliefs (Decker, Lourenco, Doll, & Hartley, 2015). These previous findings suggest that adolescents may differ from both children and adults in their ability to prospectively plan and execute goal-directed decisions and in their ability to use the outcomes they elicit to learn from their actions.

Children, adolescents, and adults may also differ in their ability to adjust their decision strategies based on their own evaluations of the efficacy of their prior interventions. Previous work has shown that when given trial-by-trial feedback about the accuracy of their causal inferences, adults adaptively upregulate their use of more effortful, discriminatory interventions in contexts in which doing so promotes more accurate hypothesis evaluation relative to other, less effortful cognitive strategies (Coenen et al., 2015). In many real-world contexts, however, individuals do not receive feedback about the quality of their interventions or the inferences they make from the resulting evidence. Rather than relying on explicit feedback, individuals may instead use their own sense of confidence in their causal inferences to determine whether they made effective intervention decisions. Confidence, however, is only a useful learning signal if it is well-calibrated to the true probability of success. In other words, adjusting one's strategy based on the perception of its efficacy will only yield strategy improvements if metacognition is sufficiently accurate. It is unclear whether, in the absence of external feedback, children, adolescents, and adults can recognize the differences in the quality of evidence elicited by previous interventions and shift their decision strategies in response to these internal evaluations of performance.

Across domains, individuals' monitoring of their cognitive performance improves throughout development (Koriat & Ackerman, 2010; Roebers, 2002; Schneider, 2008). For example, from early to middle childhood, children become better at monitoring differences in the qualities of their memories to make recognition judgments (Ghetti, Castelli, & Lyons, 2010; Ghetti, Hembacher, & Coughlin, 2013; Ghetti, Mirandola, Angelini, Cornoldi, & Ciaramelli, 2011). Similarly, throughout early childhood, individuals demonstrate an improved ability to monitor their numerical judgments, such that older children's confidence ratings more closely track the underlying difficulty of the task (Baer & Odic, 2019). In a more challenging perceptual discrimination task, the relation between individuals' decision accuracy and decision confidence strengthened from early adolescence into adulthood (Weil et al., 2013). Developmental improvements in monitoring one's uncertainty in their responses across different tasks may be driven in part by domain-specific improvements in the ability to perform the tasks themselves (e.g., encoding, numerical judgments, perceptual discrimination). However, developmental improvements in uncertainty monitoring correlate across tasks, suggesting that calibrating one's confidence judgments to the true probability of success may be a more domain-general ability (Baer, Gill, & Odic, 2019).

Metacognitive monitoring may support improvements in task performance by promoting shifts in strategy use. For example, in adulthood, individuals *use* metamemory to control future behavior, through allocating increased study time to information they perceive as having learned less well (Metcalfe & Finn, 2008) and "betting" more points on information they believe they will remember (McGillivray & Castel, 2017). It may be the case then that developmental improvements in metacognitive monitoring similarly support strategy adjustments over the course of active causal learning tasks. While children can discover and implement new response strategies in some contexts (Schuck et al., 2019), it is unclear whether they can guide their own strategy improvements during active causal learning. Prior studies have not addressed this question, in large part because many developmental studies of causal learning have used only a small number of trials. Thus, it is unclear whether children and adolescents can learn to make better interventions simply by observing the outcomes of their actions.

1.1. Characterizing developmental change in causal intervention strategies

Measuring developmental change in an ability as complex as informative intervention selection is inherently difficult. Multiple strategies can promote effective inference, so studies that have examined only the accuracy of causal judgments, or that have allowed children to freely manipulate causal systems by performing many different actions, may not effectively capture subtle changes in the ability to implement effective intervention strategies across development.

Previous research has identified two broad classes of decision strategies for making interventions: Confirmatory interventions seek information that pertains to a single hypothesis, while discriminatory interventions seek information that can disambiguate competing alternatives. A recent study of adults (Coenen et al., 2015) developed a Bayesian measurement model for determining the extent to which confirmatory versus discriminatory intervention strategies are invoked during decision-making. In this study, adults' intervention decisions were best characterized by a model that combined the discriminatory expected information gain (EIG) strategy with a confirmatory positive testing strategy (PTS) that assigned "value" to intervention decisions based on the proportion of causal links they would activate. PTS is generally less cognitively effortful than more discriminatory strategies and can yield informative outcomes in some contexts (Austerweil & Griffiths, 2011), but it can also hinder learning by failing to rule out alternative causal models (Nickerson, 1998).

The task and modeling approach used by Coenen et al. (2015) has several key properties that make them particularly well-suited to characterize changes in causal intervention strategy across development. The task itself is easy to understand but challenging to perform optimally, such that it can be understood by young children while remaining sensitive to changes in causal learning that may occur throughout late childhood, adolescence, and early adulthood. Due to the challenging nature of the task, we did not expect participants of any age to perform "at ceiling" by selecting solely the most discriminatory interventions. Thus, we could examine the emergence of "adult-like" use of a discriminatory intervention strategy—or perhaps evidence of performance exceeding that of adults—while still being able to measure differences in discriminatory strategy use among the participants in our sample. Further, by selecting problems in which PTS would be systematically less effective than EIG, we could examine whether participants of different ages had the ability to use the latter intervention strategy in a context in which it was optimal to do so.

In addition, the modeling approach can effectively capture both the more optimal, discriminatory intervention decisions, and the more cognitively simple, confirmatory strategy that may be adopted by resource-constrained learners. The model enables estimation of continuous strategy mixture weights for each participant, which can characterize the extent to which their choices reflect confirmatory or discriminatory strategies. Further, the model is sensitive to task manipulations that Coenen et al. (2015) a priori hypothesized would push people toward a more confirmatory strategy *and* toward a more discriminatory strategy. In other words, the model can capture behavior across a wide range of problems and task conditions—features that also enable it to capture differences in choice behavior across a wide range of individuals. Its sensitivity to heterogeneity in strategy use across individuals thus makes it well-suited to examine how strategy use may change across development.

Here, we leveraged the approach introduced by Coenen et al. (2015)—and its key measurement characteristics—to determine the developmental trajectories of causal learning strategies in individuals across middle childhood, adolescence and early adulthood (ages 7–25 years). Though these developmental periods have been largely neglected in the causal intervention literature, research focused on related cognitive mechanisms suggests that these periods may be characterized by robust change in learning and decision-making strategies. Beyond characterizing the general trajectory of developmental change in the use of different intervention strategies, we sought to determine whether individuals across our age range could rely on their own evaluation of the evidence elicited by their previous interventions to learn to explore more effectively over time.

2. Methods

2.1. Participants

Thirty children ($M_{\text{age}} = 10.08$ years, $SD = 1.88$ years, range = 7.0–12.98 years, 15 females), 30 adolescents ($M_{\text{age}} = 15.54$ years, $SD = 1.50$ years, range = 13.11–17.79 years, 15 females), and 30 adults ($M_{\text{age}} = 22.0$ years, $SD = 2.35$ years, range = 18.06–25.74 years, 15 females) participated in the study. One additional 6-year-old was inadvertently recruited and tested but excluded from all analyses due to falling below our age range, which we defined a priori. Our sample size was based on prior studies that examined changes in decision-making and learning across a broad age range (Decker et al., 2015; Unger, Ackerman, Chatham, Amso, & Badre, 2016). Though we discretized our sample into three age bins for recruitment and data visualization purposes, we treated age as a continuous variable in all of our analyses. Participants had normal or corrected-to-normal vision and no history of diagnosed psychiatric or learning disorders.

Participants were recruited via flyers placed around New York University, and from local science fairs and events. Based on self- or parent-report, 47.8% of participants were White, 25.6% were Asian, 13.3% were Mixed Race, 12.2% were Black, 1.1% were Native American. Additionally, 17.8% of participants identified as Hispanic. Self-reported annual household incomes ranged from under \$5,000 to more than \$100,000.

Research procedures were approved by New York University's Institutional Review Board. Adult participants provided written consent prior to participating in the study. Children and adolescents provided written assent, and their parents or guardians provided written consent on their behalf, prior to participation in the study. All participants were compensated \$20 for the 90-min experimental session, which included an additional, unrelated learning task. Participants were told that they would receive an additional bonus payment based on their performance in the causal intervention task. In reality, all participants received the same, $2.50 bonus payment.

All participants completed the matrix-reasoning and vocabulary section of the Wechsler Abbreviated Scale of Intelligence, from which age-normalized IQ scores were derived (Wechsler, 2011).

2.2. Task

Participants completed a computerized task in which they were told they were employees at a computer chip factory, whose job was to sort three- and four-node computer chips based on the configuration of their hidden wires. On each trial, participants first viewed two acyclic causal Markov graphs for 2 seconds, each of which displayed a different possible configuration of the chip's hidden wires (Fig. 1). A computer chip then appeared, with all of its nodes turned "off." Participants had as much time as they wanted to make one intervention decision—that is, to click on one node. The node that was clicked *always* turned on, as indicated by turning from its starting red color to a bright green. After a brief delay (200 ms) during which the chip dimmed and made a series of beeping noises to indicate that a selection was being processed, the chip reached its final state, indicating the outcome of the intervention. The activation of a parent node caused its direct descendants to turn on with a probability of .8. There were no background causes—Nodes could only turn on if they were directly clicked or activated by a parent node. After viewing the outcome of each intervention, participants had unlimited time to

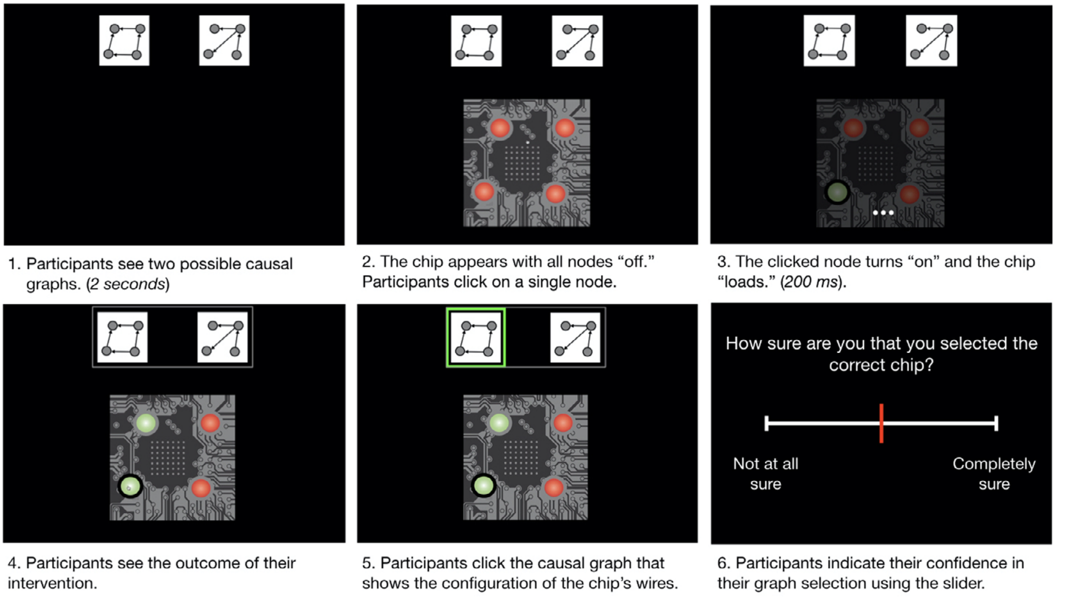

Fig. 1. Participants completed 40 intervention trials, in which they had to select a node to determine the configuration of a computer chip's hidden wires.

click on whichever of the two causal graphs they believed indicated the true configuration of the chip's hidden wires. Participants then used a continuous slider to rate their confidence that they selected the correct configuration. In Coenen et al.'s (2015) original task, participants' bonus payment depended on whether they selected the correct configuration on one randomly selected trial. To make the incentive structure easier for younger participants to understand, we simply told participants that they would be paid a bonus based on how many chips they sorted correctly.

In the original version of the task used by Coenen et al. (2015), participants were able to make multiple intervention decisions, though they lost a small amount of monetary reward each time they made an intervention. With the opportunity to make multiple interventions, different participants may have varied in their approach to their first intervention—some may have preferred to make a single, highly informative but perhaps more cognitively effortful intervention, while others may have preferred to make multiple, simpler but more monetarily costly intervention decisions. In order to avoid confounding effects of a systematic developmental bias in participants' planning over multiple intervention decisions, and to simplify the task and analysis, we restricted participants to a single intervention for each chip, as Coenen et al. (2015) did in their third experiment.

Prior to beginning the experimental trials, all participants completed an extensive tutorial in which they were trained on the probabilistic nature of the wires, the directionality of the wires, the correspondence between the causal graph diagrams and the actual chip on which they intervened, and the overall trial procedure. An experimenter remained in the testing room for the duration of the experimental session with all participants, regardless of their age.

Participants completed 40 experimental trials. Trial order was pseudo-randomized such that in each block of 10 trials, participants always completed five 3-node puzzles and five 4-node puzzles. The side of the screen on which each graph appeared was randomized. On each trial for each participant, one graph was randomly selected to be the chip's "true" underlying structure. Unlike in Coenen et al. (2015), we did not provide participants with explicit trial-by-trial feedback. Instead, participants only learned how many chips they sorted correctly at the end of the task. We did not include trial-by-trial feedback in our task both to mitigate the influence of age-related change in learning to select actions based on explicit feedback (Bolenz, Reiter, & Eppinger, 2017; Nussenbaum & Hartley, 2019) and to more closely resemble real-world causal learning contexts in which explicit feedback is often absent.

The task and its interactive instructions are available on the Open Science Framework and can be run through Psychtoolbox-3 within Matlab 2017a (Brainard, 1997): https://osf.io/cp3sj/.

2.3. Strategies

To model participant intervention choices, we focused on one specific discriminatory intervention strategy—EIG—and one specific confirmatory strategy—PTS. The models differ in how they assign value to possible interventions.

Though there are numerous possible ways to formalize both discriminatory and confirmatory intervention strategies, Coenen et al. (2015) conducted extensive comparisons across various formalizations and found that the mixture of EIG and their specification of a positive testing strategy best captured adult choices. The specification of a positive testing strategy within the context of causal learning is nontrivial, since any intervention will yield evidence that is consistent with (and therefore can serve to provide confirmatory evidence for) one of the two causal hypotheses. Coenen et al. (2015) hypothesized that participants might prefer nodes with high causal centrality, meaning nodes that activate a high proportion of causal links. Further, they hypothesized that participants would consider each individual hypothesis on its own, leading to a preference for nodes that activate a high proportion of links *within a single graph*, rather than a high proportion across graphs. Importantly, Coenen et al. (2015) tested numerous other formalizations of discriminatory and confirmatory strategies, considering, for example, a confirmatory strategy which considers the number of links within a graph that might be activated by an intervention or the total number of links across both graphs (see appendix B on p. 130 in Coenen et al., 2015). Thus, below we describe the two strategies included in their best-fitting model, which we use here to characterize developmental change in causal intervention strategies.

2.3.1. Expected information gain

Expected information gain assumes that individuals have a set of hypotheses about the structure of a particular causal system, with each system represented as a causal graphical model. A learner's uncertainty about which graph (g) is most likely the source of their current observations is represented as the Shannon entropy over the graphs within their hypothesis set (G):

$$H(G) = \sum_{g \in G} P(g) \log_2 \frac{1}{P(g)} \tag{1}$$

Learners maximizing information gain should select the intervention that will cause the largest reduction in their uncertainty. This can be computed by considering the amount of information gained by each possible outcome (o) of intervening on each node (n), weighted by their probability:

$$\text{EIG}(n) = H(G) - \sum_{o \in O} P(o|n) H(G|n,o) \tag{2}$$

where $H(G|n, o)$ is the new uncertainty after an intervention:

$$H(G|n,o) = \sum_{g \in G} P(g|n,o) \log_2 \frac{1}{P(g|n,o)} \tag{3}$$

2.3.2. Positive testing strategy

The positive testing strategy assumes that participants prefer interventions with a high causal centrality, meaning they are likely to elicit a large number of effects under a single hypothesis. We use the formalization introduced in Coenen et al. (2015), which assumes that participants choose the node (n) with the largest proportion of descendant links within a single causal graph:

$$\mathrm{PTS}(n) = \max_g \left(\frac{\mathrm{DescendantLinks}_{n,g}}{\mathrm{TotalLinks}_g} \right) \tag{4}$$

where "DescendantLinks" refers to the number of links (or in the task context, wires) originating at a particular node and "TotalLinks" refers to the total number of links within a particular causal graph.

2.4. Mixture model

To characterize participants' intervention choices, we fit a mixture model in which we assumed participants were linearly combining EIG and PTS with weight θ, where $\theta = 0$ indicates a pure PTS strategy and $\theta = 1$ indicates a pure EIG strategy (Coenen et al., 2015). Thus, the "value (V)" of a given intervention (n) can be described as:

$$V(n) = \theta \times \mathrm{EIG}(n) + (1 - \theta) \times \mathrm{PTS}(n) \tag{5}$$

2.5. Choice function

We assumed that participants' choices were noisy, such that the expected value of each intervention probabilistically influenced intervention decisions. We used a softmax choice function (Luce, 1959) to represent this process, with a free parameter, τ, to capture each participant's decision noise, such that the probability of selecting each node (n) is:

$$P(n) = \frac{\exp\left(\frac{V(n)}{\tau}\right)}{\sum_i \exp(V(n_i)/\tau)} \tag{6}$$

2.6. Problem selection

We selected three- and four-node problems for inclusion in the task so that across problems, PTS was systematically less effective than the discriminatory EIG strategy (Table 1). On any given set of problems, EIG will always be at least equally effective as PTS in eliciting evidence that can disambiguate two competing causal hypotheses. However, the difference in the efficacy of these strategies varies depending on the specific causal learning problems; in some cases, PTS will be almost as effective as EIG. Because our goal was to examine developmental differences in individuals' *abilities* to make

Table 1
Average posterior probability of the most likely graph after a single intervention with a given strategy

	Noise Level					
Strategy	$\tau = 0.01$	$\tau = 0.2$	$\tau = 0.5$	$\tau = 1$	$\tau = 1.5$	$\tau = 3$
EIG	0.92	0.89	0.84	0.80	0.78	0.77
PTS	0.75	0.78	0.77	0.77	0.76	0.76
Random	0.75	0.75	0.75	0.75	0.75	0.75

discriminatory interventions, and not differences in "default" or "baseline" exploration strategies, we "stacked the deck" in favor of the more effortful and more consistently effective discriminatory strategy.

In addition, we selected problems such that the values assigned by EIG and PTS to each node differed to the greatest extent possible. Finally, we ensured that the node to which each strategy assigned the greatest value was roughly equally distributed across node positions.

3. Results

3.1. Age-related change in strategy use

First, we examined the relation between age and IQ in our sample through a linear regression. Here and for all subsequent models, we standardized (z-scored) age across our sample. There was no significant relation between age and IQ, $F(1, 88) < .001$, $p > .99$, $\eta_p^2 < .001$, indicating that our analyses of the effects of age on causal learning are not confounded by systematic developmental differences in intelligence. All effects reported in the manuscript hold when controlling for IQ (see Appendix S1 for full results).

We next examined how strategy use varied as a function of age by fitting participant choices with our mixture model. The two previous studies using this modeling approach employed a hierarchical model in which group-level hyper-parameters were also estimated (Coenen et al., 2015; Meng et al., 2018), but given our broad age range, we did not want to assume that the participants in our sample were drawn from a single, population-level distribution. Rather than estimating group-level hyper-parameters, we estimated the model separately for each participant. Full details of the model-fitting procedure and parameter recoverability analyses are included in Appendix A and Appendix S1, respectively. In addition, we report details of a hierarchical Bayesian model that directly estimates the influence of age and quadratic age on strategy mixture weights and decision noise in Appendix S1.

To characterize how strategy use changed with age, we extracted the posterior mean estimates of strategy mixture weights (θ) and examined their relation with age. We tested two linear regression models to examine linear and nonlinear trajectories of developmental change: One included linear standardized age as a predictor, and one included both linear standardized age and quadratic standardized age as predictors. The inclusion of a quadratic age term is a common approach in developmental studies to examine nonlinear patterns of age-related change (e.g., Braams, van Duijvenvoorde, Peper, & Crone, 2015; Mills et al., 2016; Somerville et al., 2013; van den Bos, Rodriguez, Schweitzer, & McClure, 2015). We followed this approach for all subsequent models described in the paper.

The model with the quadratic age term provided a significantly better fit to the data, as indicated by a one-way analysis of variance, $F(1, 87) = 10.4$, $p = .002$. Both age ($\beta = 0.14$, $p < .001$, $\eta^2_p = 0.33$) and quadratic age ($\beta = -0.07$, $p < .002$, $\eta^2_p = 0.11$) predicted strategy mixture weight (Fig. 2), suggesting that through early adolescence, participants decreased their use of PTS in favor of EIG. Even within age groups, however, strategy use varied across problems (Fig. 3); adolescent choices, for example, sometimes resembled those of adults (Fig. 3; Problem 19) and sometimes were more like those of children (Fig. 3; Problem 18).

We also examined how decision noise (τ) changed with age. As with θ, we extracted the posterior mean estimates of τ for each participant and examined their relation with age. As before, we ran two separate linear regressions: one with age as a predictor and one with both age and quadratic age as predictors. First, we examined whether the model including quadratic age provided a significantly better fit to the data. It did not ($p = .40$), so we removed the quadratic age term from the model and examined the relation between linear age and decision noise. Linear age did not predict decision noise ($\beta = -0.22$, $p = .32$, $\eta^2_p < 0.01$), suggesting that the strength with which the value predictions of the mixture model captured choice behavior did not significantly differ across our age range (Fig. 2). Further, there was no significant relation between θ and τ ($\beta = -0.01$, $p = .52$, $\eta^2_p < 0.01$), suggesting that age-related change in strategy mixture weight cannot be attributed to age-related differences in decision noise.

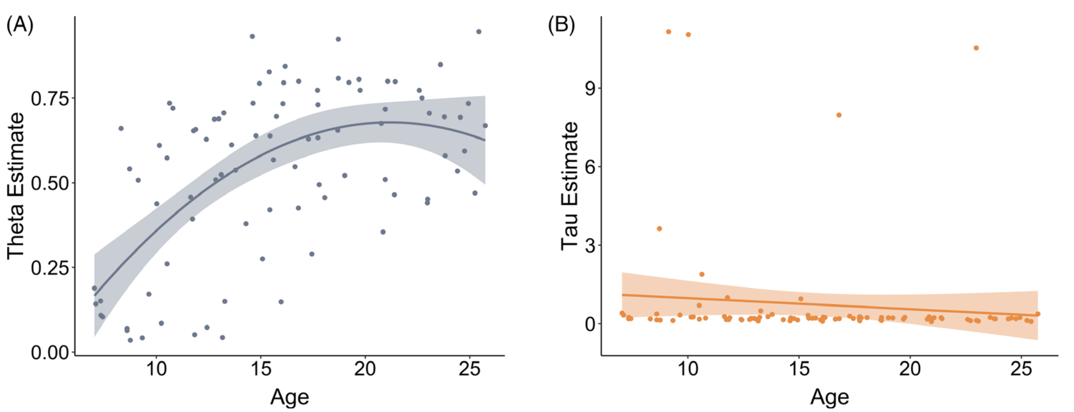

Fig. 2. (A) Model-derived estimates of participants' strategy mixture weights (θ) show that participants became more discriminatory with increasing age through late adolescence. (B) Decision noise estimates (τ) show that decision noise did not systematically vary with age. Best-fitting regression lines illustrating the effects of age and squared age on θ and age on τ are plotted.

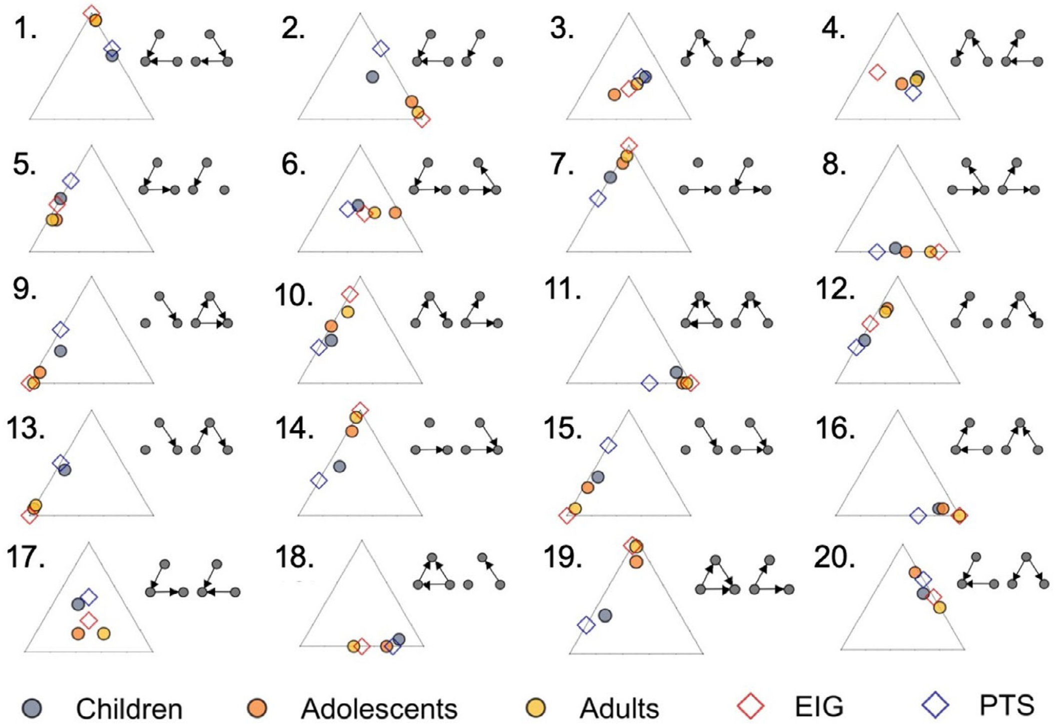

Fig. 3. Intervention choices for the 20 three-node puzzles presented in the experiment. The corners of each simplex represent nodes on which participants intervened. Points within each simplex correspond to the probabilities of intervening on each node. Points at the middle of the simplex indicate that participants were equally likely to intervene on each node, while points at the corners indicate that one node was strongly favored. The colored circles represent the choice probabilities for each age group (children: 7–12 years old; adolescents: 13–17; adults: 18–25), while the diamonds represent the probabilities of intervening on each node as determined by use of a "pure" expected information gain (EIG) and positive testing strategy (PTS), without decision noise. On Problem 1, a learner following a pure EIG strategy will select the top node, whereas a learner using PTS will sometimes select the top node and sometimes select the bottom right node. Adolescents and adults were very likely to select the top node. Whereas some children selected the top node, some selected the bottom right node.

In line with previous findings, our modeling results suggest that children (Meng et al., 2018) and adults (Coenen et al., 2015) use a combination of confirmatory and discriminatory strategies to test causal hypotheses. Moreover, the relative mixture of this combination systematically changes across adolescence.

3.2. Inference–intervention interactions

Why did the use of a discriminatory intervention strategy increase across development? One possibility is that when presented with the novel task, participants explored different intervention strategies until finding one they believed was most effective. Older participants may have been more sensitive to the relative efficacy of different intervention strategies, enabling them to adjust their decisions throughout the course of the task. Importantly, for EIG to be an effective strategy, individuals need to be able to make accurate causal inferences based on the outcomes of their interventions. Gaining information to disambiguate competing hypotheses is only useful if individuals can correctly update their beliefs based on that new evidence (Coenen & Gureckis, 2015). We thus used causal inference ability as a metric for the relative efficacy of EIG over PTS.

To examine how causal inference changed with age, we computed the posterior probabilities of each of the two possible causal graphs based on the selected node and the final states of the other nodes on each trial. We then ran a linear mixed-effects model, implemented through the "afex" package in R (R Core Team, 2018; Singmann, Bolker, Westfall, & Aust, 2016) with random participant intercepts to determine whether there was a relation between age and the posterior probability of the structure selected. We tested the significance of the effects of age and quadratic age on the posterior probability of the structure that was selected using an F test with Kenward–Roger approximations for degrees of freedom.[1] Our best-fitting model included both a linear and quadratic effect of age, $\chi^2(2) = 17.5$, $p < .0001$. We found main effects of age ($F(1, 87) = 33.9$, $p < .0001$) and quadratic age ($F(1, 87) = 18.7$, $p < .0001$). This suggests that with increasing age, throughout childhood and into early adolescence, individuals became better at evaluating the outcomes of their interventions to disambiguate competing hypotheses. However, this metric is inherently confounded with intervention decisions—by definition, interventions with higher EIG scores are more likely to lead to greater increases in the posterior probability of one structure over another.

Participant confidence in the structure they selected can also provide insight into developmental change in causal inference—and metacognitive sensitivity to causal evidence—without being confounded by intervention choice. If participants were sensitive to the extent to which the information they gained allowed resolution of competing hypotheses, then their confidence in the structures they selected should track the posterior probability of their choice. We first ensured there were no systematic differences in how participants across our age range used the confidence scale (see Appendix S1). To determine how these posterior probabilities and age influenced confidence ratings, we ran a linear mixed-effects model with random intercepts for each participant. Our best-fitting model included both a linear and quadratic effect of age, $\chi^2(2) = 86.0$, $p < .001$. Participants were more confident in their selection when the posterior probability of the structure they selected was higher, $F(1, 3562.6) = 759.4$, $p < .001$. However, this effect was qualified by an age $\times$ posterior probability interaction ($F(1, 3567.6) = 91.8$, $p < .001$) as well as by a quadratic age $\times$ posterior probability interaction ($F(1, 3573.6) = 85.3$, $p < .001$), such that the influence of posterior probabilities on confidence ratings increased throughout childhood and early adolescence. These results indicate that the ability to evaluate the extent to which new information supported causal hypotheses improved nonlinearly across development. Importantly, they suggest that there are developmental improvements in causal inference that are separable from improvements in intervention strategy.

We next examined whether differences in causal inference influenced intervention strategy. Specifically, we computed the correlation between the posterior probability of the structure selected and confidence ratings on each trial for each participant and ran a linear regression to determine whether these values, which we will refer to as "evidence sensitivity," predicted individuals' strategy mixture weights. We found a positive relationship between evidence sensitivity and strategy mixture weight ($\beta = 0.11$, $p < .001$, $\eta_p^2 = 0.25$), even when controlling for age. In other words, participants with stronger sensitivity to the strength of the evidence on which to base their inferences also demonstrated greater use of EIG. We also observed an age × strategy mixture weight interaction effect ($\beta = -0.04$, $p = .03$, $\eta_p^2 = 0.05$), such that the strength of the relation between evidence sensitivity and strategy mixture weight decreased with increasing age.

3.3. *Within-task learning effects*

Beyond examining how causal intervention strategy changed with age, our use of 40 trials enabled us to examine learning over the course of the task. We hypothesized that older participants' greater use of a discriminatory strategy might in part be driven by faster learning, such that age would more strongly influence estimates of strategy mixture weights in the second half of the experiment, after participants had the opportunity to learn to adjust their strategy based on their evaluations of their earlier decisions.

To examine whether participants used a different mixture of strategies throughout the course of the task, we fit our Bayesian model separately to the first and second half of the trial data for each participant. We then ran a linear mixed-effects model to determine how experiment half and age influenced strategy mixture weight. As before, both linear and quadratic age predicted strategy mixture weight (*p*s $< .01$). Furthermore, strategy mixture weight increased from the first half to the second half of the experiment, $F(1, 87) = 9.1$, $p = .003$ (Fig. 4), indicating that participants may have learned to use a more discriminatory strategy over the course of the task. Contrary to our prediction, however, experiment half did not interact with age or squared age (*p*s $> .20$).

Decision noise also decreased over the course of the experiment, $F(1, 88) = 5.5$, $p = .02$. This effect was qualified by an age × experiment half interaction, such that younger participants demonstrated a greater decrease in decision noise from the first to the second half of trials, $F(1, 88) = 5.5$, $p = .02$ (Fig. 4). Further, we also observed a main effect of age on decision noise, $F(1, 88) = 7.3$, $p = .008$. This suggests that younger participants may have learned to use their estimates of the value of each intervention to more strongly guide their decisions over the course of the task. While the change in their strategy mixture weight did not statistically differ from that of older participants, younger participants may have become more systematic in their interventions, even if they did not execute the more optimal strategy.

Finally, we examined whether participants' evidence sensitivity related to their change in strategy use over the course of the task. We hypothesized that participants who were most sensitive to the efficacy of their intervention choices would also demonstrate the greatest increase in their use of a discriminatory strategy over the course of the task. To test this prediction, we computed $\Delta\theta$ for each participant by subtracting their estimated strategy mixture weight value over the first half of the experiment from their estimated

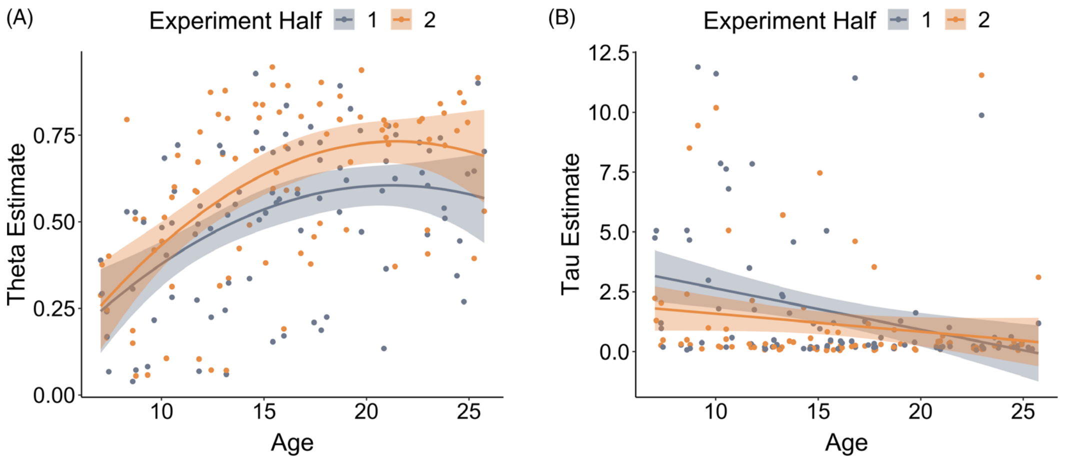

Fig. 4. In the second half of the experiment, participants relied more on expected information gain over positive testing strategy (A), and their choices were less noisy (B). Best-fitting regression lines illustrating the effects of age and squared age on θ and age on τ are plotted.

value over the second half of the experiment. We then ran a regression examining the effects of age and evidence sensitivity on $\Delta\theta$. We found a significant effect of evidence sensitivity on $\Delta\theta$ ($\beta = 0.07$, $p = .007$, $\eta_p^2 = 0.08$), such that participants who were most sensitive to the strength of evidence they elicited in favor of a causal hypothesis demonstrated increased use of EIG over the course of the experiment. Mirroring our previously reported results, there was no significant effect of age on $\Delta\theta$, nor was there an age × evidence sensitivity interaction effect ($ps > .59$). These results thus indicate that across our age range, metacognitive sensitivity to the efficacy of different intervention decisions promoted better decision-making over the course of the experiment.

4. Discussion

Our results demonstrate robust changes in causal intervention strategy use from middle childhood to adulthood. We found that interventions became more discriminatory throughout childhood and early adolescence, while the rate at which intervention strategies changed with age slowed throughout late adolescence and early adulthood. What causes this developmental shift?

One possibility is that individuals monitor the quality of evidence they have elicited from their past interventions and learn to adjust their decision-making strategies over time. Participants in our study who demonstrated the highest sensitivity to the efficacy of their previous interventions also showed the greatest increases in the use of a discriminatory strategy from the first to the second half of the experiment. It is possible that this learning mechanism operates not just on short timescales, but also throughout development, leading to broad shifts in intervention strategies as individuals accumulate more experience and become better able to monitor the efficacy of their actions (Weil et al., 2013). Interestingly, however, the youngest participants in our sample demonstrated poor evidence sensitivity, suggesting they may not be able to determine the efficacy of different interventions. While it may be the case that younger children had difficulty in translating their internal sense of confidence to the external response scale, our findings align with other work that suggests that both uncertainty monitoring (Koriat & Ackerman, 2010; Roebers, 2002; Schneider, 2008) and the ability to make accurate causal inferences improves from childhood to adulthood (Gopnik et al., 2017). Without the ability to judge the strength of the causal evidence they elicited and monitor their own intervention performance, children may benefit the most from explicit feedback about the quality of their interventions. Future studies should examine this idea more directly, by examining how external feedback may shape metacognitive sensitivity and interact with self-directed learning to promote more discriminatory interventions across development.

In addition, future studies could tease apart the role of causal inference and metacognitive sensitivity by more directly measuring participants' causal inference abilities. In our study, we tested causal interventions and causal inference within the same task. This meant that participants did not all receive the same tests of inference—participants who made better interventions often had easier inference problems because their interventions elicited a greater difference in the evidence in support of each causal graph. Future work could overcome this limitation of our design by including a separate measure of causal inference or a yoked condition in which participants make causal judgments based on the evidence elicited by a different participant's interventions. These designs would enable the derivation of a measure of causal inference that could be more directly compared across participants, and they could clarify the relations between causal inference, evidence sensitivity, and improvements in strategic information-seeking. It may be the case that metacognitive sensitivity to the quality of evidence elicited by one's interventions follows a similar developmental trajectory as causal inference. Alternatively, as has been demonstrated in different domains, the ability to make accurate decisions may follow a trajectory independent from that of the ability to calibrate one's certainty judgments (Baer et al., 2019). By more cleanly separating these two abilities, future work could more directly test how both relate to improvements in causal intervention strategy.

Though the youngest participants in our sample demonstrated worse evidence sensitivity, they also demonstrated the greatest reduction in decision noise from the first to the second half of the experiment. This suggests that their interventions became more systematic over time. In line with our qualitative results, which show that children's interventions often align with the predictions of PTS, this finding indicates that younger participants may have learned to execute a specific, confirmatory strategy over the course of the task. Coenen et al. (2015) found that adults shifted toward PTS when under time constraints, suggesting it may be a useful strategy for resource-constrained learners. Our developmental findings similarly support this idea: Children, whose cognitive capacities are more limited than adults, don't behave randomly, but rather may learn to rely on a specific intervention strategy that demands fewer cognitive resources than a more discriminatory approach.

The developmental trajectory that we observed mirrors other patterns of learning across childhood and adolescence, suggesting that more general improvements in learning and decision-making mechanisms may support the selection of informative interventions across development. Across multiple contexts, the ability to strategically control information-seeking improves throughout late childhood and early adolescence. For example, in one study, participants had to choose between different probabilistic slot machines to earn reward across contexts with different temporal horizons. With increasing age, participants (ages 12–28 years) made decisions that demonstrated greater sensitivity to the increased utility of gaining information when they had more time to act on that information in the future (Somerville et al., 2017). In another set of studies examining value-based decision-making, researchers found that the ability to recruit and use a mental model of the transition structure of the environment to make decisions also improved throughout childhood and adolescence, and into young adulthood (8–25 years; Decker et al., 2016; Potter, Bryce, & Hartley, 2017). Similar patterns of change are observed outside of the value-learning domain: In a study of question-asking, the efficiency with which individuals narrowed the hypothesis space improved from ages 7 to 18, suggesting increasing recruitment of more complex, information-seeking strategies (Rugerri & Lombrozo, 2015). Though decisions about causal interventions may have properties that make them distinct from other forms of information-seeking, the similar developmental trajectories observed across diverse studies suggest that common underlying mechanisms may support the development of strategic decision-making across domains.

The ability to plan decisions may be one such candidate mechanism. It may be the case that with increasing age, individuals become better at prospectively considering and planning their interventions. Though evidence sensitivity correlated with strategy mixture weight in our data, it did not fully account for developmental change in strategy use. Importantly, we hypothesized that the ability to make accurate causal judgments may enable individuals to select the best intervention only if they prospectively simulate and sample the outcomes of potential choices (Bonawitz, Denison, Griffiths, & Gopnik, 2014). On some trials, participants may not have attempted to think through the possible outcomes of their decisions, in which case the ability to evaluate those outcomes would not affect the intervention choice. Future studies should probe the role of other cognitive mechanisms in supporting the use of EIG, like model-based decision-making, which may support or similarly rely on simulating probabilistic outcomes of multistage decisions (Decker et al., 2016; Doll, Duncan, Simon, Shohamy, & Daw, 2015).

Another possibility is that younger people are equally *capable* of implementing a more discriminatory intervention strategy but perform a different cost–benefit analysis when determining which strategy to use. We tried to isolate developmental differences in ability from developmental differences in default strategy tendencies by selecting problems in which EIG was systematically more effective at eliciting disambiguating evidence, limiting participants to a single intervention, and incentivizing causal inference accuracy. However, the younger participants in our study may still have been biased to use the less effortful confirmatory strategy despite being *able* to perform more discriminatory interventions. As mentioned previously, confirmatory strategies like PTS often reveal diagnostic information in environments in which causal links are sparse or deterministic (Austerweil & Griffiths, 2011). Additionally, confirmatory hypothesis testing may be adaptive when individuals have the opportunity to make multiple interventions at low cost. Rather than spending time and cognitive effort to make the single best intervention, children prefer to make multiple, easier, intervention decisions, which together provide the information they need. Repeated experiences in learning contexts that offer the opportunity to make multiple interventions may thus bias children toward confirmatory interventions, such that they continue to perform them even when doing so is no longer adaptive. Alternatively, if individuals know that they are limited in their ability to correctly infer causal structure regardless of the quality of evidence they observe, then using the costlier EIG strategy is actually maladaptive. Thus, even within the experimental context in which there is *not* the opportunity to make multiple interventions, children's use of a more confirmatory strategy may actually reflect a rational use of cognitive resources (Lieder & Griffiths, 2017). Future studies could isolate changes in *ability* from changes in effort allocation, by raising the cost of making an uninformative intervention or forcing all participants to spend a long time deliberating prior to allowing them to perform their intervention.

Finally, though few studies have examined causal learning in adolescence, our results demonstrate that causal learning and decision-making continue to change during this period. This finding contributes to the growing body of literature examining how the ability to effectively support one's own learning changes over developmental time (Kachergis, Rhodes, & Gureckis, 2017; Ruggeri, Markant, Gureckis, Bretzke, & Xu, 2019). Future work probing the cognitive mechanisms that drive these changes will inform our understanding of how children and adolescents shape their own learning opportunities as they interact with their environments with increasing independence.

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Open Research badges

This article has earned Open Data and Open Materials badges. Data and materials are available at https://osf.io/cp3sj/.

Data Availability Statement

All data and analysis code are available on the Open Science Framework: https://bit.ly/2EsyVBd.

Note

1. Kenward–Roger approximations can lead to non-integer degrees of freedom.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article:

Appendix S1. Supplementary Analyses.

Appendix A: Model fitting procedure

A.1 Model fitting details

A.1.1 Mixture model

We specified and fit our mixture model using the brms package in R (Bürkner, 2017). We estimated posterior distributions over the parameters using Markov chain Monte Carlo (MCMC) sampling via dynamic Hamiltonian Monte Carlo (HMC) implemented in

Stan (4 chains of 2,000 iterations, 1,000 per chain discarded as warm-up; 4,000 total samples per parameter; Stan Development Team, 2019). We used a noninformative prior for $\theta(\beta(1, 1))$ and a weakly informative prior for $\tau{:}(\gamma(1, 0.1))$. Folded, rank-normalized, split R values for all parameter estimates were <1.01, indicating convergence across chains (Vehtari et al., 2019). Both bulk effective sample sizes and tail effective sample sizes were >400 (Vehtari et al., 2019) for every parameter estimate (bulk ESS: $\tau_{min} = 1{,}510$, $\tau_{mean} = 4{,}233.6$; $\theta_{min} = 1{,}514$, $\theta_{mean} = 3{,}451.6$; tail ESS: $\tau_{min} = 599$, $\tau_{mean} = 2{,}489$; $\theta_{min} = 653$, $\theta_{mean} = 1{,}799.4$).

A.1.2 Mixture model split by experiment half

We specified and fit our mixture model as described above. Here, we used four chains of 5,000 iterations, 2,500 per chain discarded as warm-up; 10,000 total samples per parameter. Folded, rank-normalized, split R values for all parameter estimates were <1.01, indicating convergence across chains. Both bulk effective sample sizes and tail effective sample sizes were greater than 400 for every parameter estimate (bulk ESS: $\tau_{min} = 2{,}776$, $\tau_{mean} = 8{,}953.8$; $\theta_{min} = 4{,}815$, $\theta_{mean} = 9{,}882$; tail ESS: $\tau_{min} = 1{,}122$, $\tau_{mean} = 5{,}089.5$; $\theta_{min} = 1{,}688$, $\theta_{mean} = 4{,}963.4$).