Children's developing understanding of learning as improvement over time

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Abstract

How do children – who are undeniably productive learners – think about their learning? Do children understand, as adults do, that learning is a process of continuous improvement over time? To explore children's emerging representations of the learning process, we created a non-verbal motor learning paradigm where 4- to 8-year-olds predicted their own learning curve without prior experience. We found that by age 7, children predicted improved performance over time. Younger children, however, were overly optimistic about how well they would do at the game and often predicted near-perfect performance across trials. This work suggests that children's predictions of their future learning curve become more accurate with age, which may have implications for young children's learning decisions.

Keywords: motor learning; metacognitive reasoning; optimisim

Introduction

Children are powerful and productive learners, able to infer abstract concepts from just a few examples (Bonawitz et al., 2011; Griffiths, Sobel, Tenenbaum, & Gopnik, 2011; Gweon & Schulz, 2011; Schulz, Bonawitz, & Griffiths, 2007; Tenenbaum, Kemp, Griffiths, & Goodman, 2011; Xu & Tenenbaum, 2007). But how do children *think* about their own remarkable learning? At a very basic level, it is unknown whether children think of learning as a process of getting better over time. Critically, how children think about learning could have downstream consequences for their actual learning. For instance, if a child expects to learn a difficult task right away, then they may give up on the task prematurely when they do not perceive immediate progress. Here we seek to examine how children represent learning as a process of improvement over time.

Learning can often be described with a "learning curve" - a measure of performance over time. Work on skill learning has shown that learning curves are best fit with an exponential decay function (Luft & Buitrago, 2005; Heathcote, Brown, & Mewhort, 2000; Krakauer, Hadjiosif, Xu, Wong, & Haith, 2019). That is, when learning a new skill, people usually make rapid progress early on and then their performance plateaus (Luft & Buitrago, 2005; Mazur & Hastie, 1978). Adults seem to intuit that skill learning unfolds exponentially: When introduced to a novel motor learning task, adults correctly predict that a naive learner's trial-by-trial performance would follow an exponential decay function without having any first-hand experience with the task (Zhang, McDougle, & Leonard, 2022). Thus adults not only represent learning as a process, but they also correctly represent the specific shape of certain learning curves. However, less is known about when children start to develop an understanding of how learning unfolds over time.

To our knowledge, only one study so far has directly probed how children think about the concept of "learning". In this study, Sobel and Letourneau (2015) asked 6- to 10-year-old children to verbally reflect on their own learning experiences. They found that when describing what "learning" means, 6- to 10-year-olds use more process-based responses (e.g., references to sources of learning, or specific strategies for learning) than 4- to 5-year-olds. This work suggests that, by age 6, children begin to think that learning is a process involving the transmission of information or practice. However, these results raise the question of how children think about the learning process on a more fine-grained level. For example, do children think, as adults do (Zhang et al., 2022), that skill learning unfolds gradually over time rather than instantaneously? Furthermore, given that Sobel and Letourneau (2015) used a verbal paradigm, it is unknown whether younger children, who have limited verbal abilities, might show more sophistication in their thinking about learning on a non-verbal task.

Prior research suggests that children younger than 6 can represent aspects of their learning process. For example, 20-month-olds successfully monitor their uncertainty and selectively ask their caregiver for help when encountering a challenge (Goupil, Romand-Monnier, & Kouider, 2016). Preschoolers can also represent their uncertainty and use this information to effectively guide their future exploration (Lapidow, Killeen, & Walker, 2022; Baer & Kidd, 2022; Ghetti, Hembacher, & Coughlin, 2013). Furthermore, when given information about their past performance, 4- to 6-year-olds are more likely to stick with a challenge when their performance has improved over time versus stayed the same, suggesting that children are sensitive to the rate of their past performance (Leonard, Cordrey, Liu, & Mackey, 2022).

On the other hand, when given the opportunity to predict future performance or learning, young children tend to be overly optimistic. For example, even after demonstrating that

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they remember their poor prior performance on a jumping task, 4-year-olds continue to overestimate their future jumping distance more than 6-year-olds (Schneider, 1998). By age 10, children still overestimate how much they can learn about a novel object by self-exploration, despite actually failing at the task (Richardson, Sheskin, & Keil, 2021). Additionally, school-aged children express greater degrees of optimism when judging how much knowledge can be learned in just one year (Lockhart, Goddu, & Keil, 2021). Thus, children's overly optimistic expectations of their abilities may prevent them from representing learning as a process of improvement, since they may be biased to predict instantaneous and constant success.

Current Experiment

To better understand children's intuitions about the learning process, we tasked 4- to 8-year-old children to think about their own performance over time (their "learning curve") using a novel motor learning paradigm. We focused on 4- to 8-year-olds, a similar age range as in Sobel and Letourneau (2015), to explore whether a simplified non-verbal paradigm would reveal similar developmental trends in children's intuitions about the learning process. Our paradigm is unique in that it is the first to probe children's trial-by-trial predictions of performance over time without feedback. This approach allowed us to investigate whether children's intuitions about their future performance could be characterized by improvement over time without being biased by their own performance.

In our preregistered experiment (link), we introduced children to a game in which the goal was to toss bean bags onto a target on the floor. To make the game novel and challenging, we had children toss the bean bag with their feet (like in hacky sack) instead of their hands. The game apparatus included a large mat with a coordinate grid and a red target in the center (see Figure 1a). Children made predictions about where their first five tosses would land by physically placing bean bags on the mat. Once placed, each bean bag stayed on the mat to lower memory demands of tracking performance over time. Using the grid on the mat, we recorded the coordinates of each bean bag and calculated the Euclidian distance from the bean bag to the center of the target. With this information, we were able to reconstruct each child's precise predicted learning curve. After children made predictions, we let them play the game for five trials to measure their actual performance. Although prior work shows that the beginning of motor skill learning curves follows a steep linear trend (Heathcote et al., 2000; Solum, Lorås, & Pedersen, 2020), we were unsure whether children in our task would actually improve across the five trials given that testing occurred in a busy environment on a science museum floor. However, our key hypotheses concerned how children think about their performance over time, not how they actually perform. Specifically, we hypothesized that children would predict that their performance would get better across trials (i.e., the bean bags would get closer to the center). We also hypothesized that younger children would predict better performance on average compared to older children due to their optimistic expectations, which could result in flatter predicted learning curves.

Method

Participants. We collected a preregistered sample of 125 4- to 8-year-old children (25 children per age group, binned by year) at two local children's museums. Based on parental report, 55.2% of participants were female, 42.4% were male, and 2.4% preferred not to answer. The racial and ethnic makeup of the participants was as follows: 49% White, 19% Asian, 19% Hispanic/Latino, 10% multiracial, 8% Other, 5% Black or African American, 0.8% American Indian or Alaskan, 0.8% Native Hawaiian or other Pacific Islander, and 10% preferred not to answer. An additional 16 participants were excluded from further analyses based on preregistered criteria: child opting out ($n = 6$), child's predictions were moved before they could be recorded ($n = 5$), experimenter error ($n = 2$), ASD diagnosis ($n = 2$), and outside interference ($n = 1$).

Stimuli. This experiment included an 80×85 inch gridded mat (with 30×30 1.3-inch squares) with a red circular target in the middle (3.9-inch radius). The canvas also contained a larger red ring (15.6-inch radius) around the target, as well as blue-dotted intervals across each axis (6.5 inches apart). This experiment included five 4×4 inch bean bags weighing 6 ounces each, labeled with numbers 1 through 5 on both sides.

Procedure. This experiment had three phases. First, the experimenter explained that the participant was going to play a new game with the goal of landing bean bags in the center of the mat (see Figure 1a). Before continuing, the participant was asked to restate the goal of the game. The experimenter then walked the participant to a line taped 8 feet away from the mat's lower edge and explained that they needed to toss the bean bag from behind the line. However, instead of tossing with their hand, the experimenter explained that they needed to toss the bean bag with their foot. The experimenter demonstrated placing the bean bag on top of their foot and tossing the bean bag toward the participant. To gain an understanding of this tossing method, children were allowed to make one practice toss toward an experimenter standing 2 feet to the right of the child. The practice toss was intentionally directed away from the mat to avoid any anchoring effect on children's predictions of their performance.

Next, the participant made predictions about where their tosses would land (Figure 1b). In an attempt to limit task demands and speed up testing for families visiting the children's museum, we only asked each participant about their first five tosses. For each toss, the experimenter asked the participant to close their eyes and imagine tossing the bean bag toward the target. The experimenter asked, "Where do you think your (first, next, last) toss will land?". Children were prompted to walk on the mat and place a bean bag (numbered based on trial) down to mark each of their predictions. All five bean

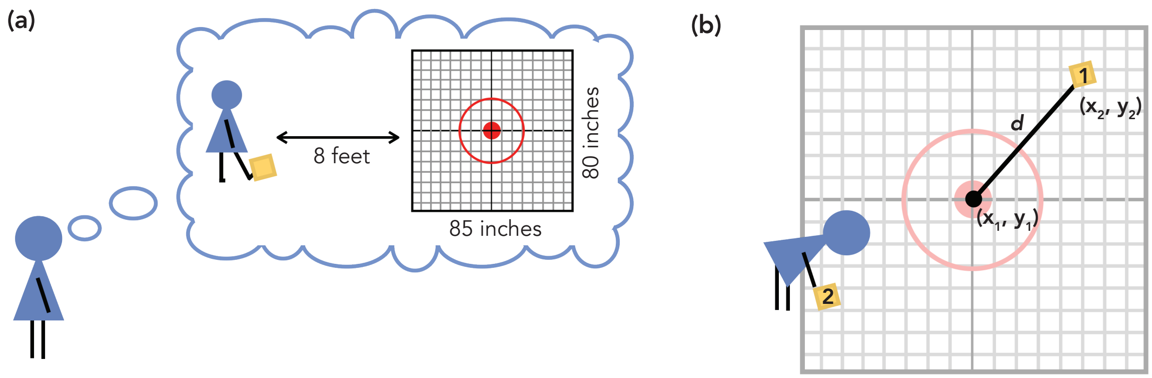

Figure 1: Schematic of bean bag toss game. (**a**) Children were introduced to a game where they had to stand 8 feet away from a mat and use their feet to toss a bean bag toward the center of the mat (in red). They were asked to make predictions about where they thought their tosses would land. (**b**) Children made predictions about where their first five tosses would land by placing numbered bean bags directly on the target grid. The Euclidean distance (d) between each bean bag location and the center of the grid was calculated using $d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$ to reconstruct individual children's predicted and actual learning curves.

bags were left on the mat during this prediction phase. To see whether children's predicted learning curves reflect their perceived task difficulty, participants answered two successive questions about perceived difficulty, "Do you think landing a bean bag in the center of the target with your foot is easy or hard?" and "Do you think it is kind of easy/hard or really easy/hard?" (coded as an ordered array, from really easy, kind of easy, kind of hard, to really hard). The experimenter took a photo of the predictions and cleared them off the floor.

In the last phase, the participant stood behind the colored tape and used their foot to toss five bean bags. The experimenter again took a photo of the tosses and thanked the child for participating.

Coding. The horizontal and vertical locations for the bean bags were coded based on photos of the mat. In the case that a bean bag landed outside the mat (5.6% of predicted tosses and 72.2% of actual tosses), measurements were taken by the experimenter at the time of testing using a tape measure (from the center of the bean bag to the edge of the grid). All X,Y coordinate data were double-scored by a coder blind to child participant age and hypotheses (note that bean bags that landed off the mat could not be double-scored). A third coder arbitrated discrepancies over 1 inch between the two coders (note that the bean bags were 4 by 4 inches, much larger than the grid units of 1.3 by 1.3 inches, and thus we allowed discrepancies under 1 inch in measurement). Coder scores were highly correlated ($r = .997$, $p < .001$). Next, the Euclidean distance was calculated based on the X- and Y-axis locations: $d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$. Predicted and actual learning curves were operationalized as the minimization of the Euclidean distance between the bean bag's landing location and the target center across five trials.

Results

Performance predictions

On average, children did not think their performance would improve across five trials: A linear mixed-effects model predicting children's predicted performance (in Euclidean distance) with trial and random effects for participant revealed a non-significant trend effect of trial ($b = -.81$, $p = .07$). However, as predicted, we found that age was related to performance predictions: When age in months was added to the model, there was a positive main effect ($b = .18$, $p = .002$), showing that younger children predicted better average performance (i.e., bean bags landing closer to the center) than older children. We also found that the slope of children's predicted learning curves differed by age. A linear mixed-effects model predicting children's predicted performance with a trial by age interaction and random effects for participant revealed a significant interaction ($b = -.11$, $p < .001$; see Figure 2). Follow-up analyses within each age bin predicting children's predicted performance by trial revealed that 4-year-olds thought their performance would get worse across five trials ($b = 1.18$, $p_{FDR-corrected} = .02$), and 5- to 6-year-old children did not predict their performance would significantly change across trials ($b > .006$, $p_{FDR-corrected} > .16$). However, 7- and 8-year-old children predicted their performance would improve across trials (7-year-olds: $b = -2.81$, $p_{FDR-corrected} = .008$; 8-year-olds: $b = -3.62$, $p_{FDR-corrected} = .02$). Thus, our data show that by age 7, children predict that their performance will improve across trials.

Percieved difficulty

Children's perceived task difficulty related to their performance predictions. Results from a linear mixed-effects model predicting predicted performance using children's difficulty judgments (4 levels) and random effects by trial, participant,

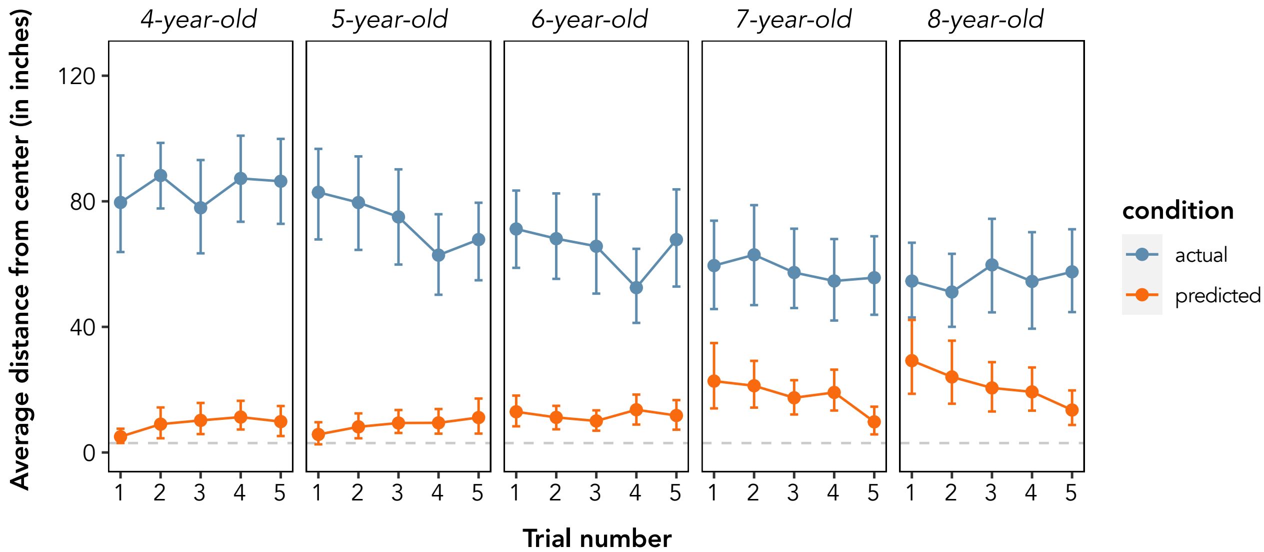

Figure 2: Children's average actual (blue) and predicted (in orange) bean bag toss performance across five trials by age groups. The dashed gray line indicates the distance from the edge of the red target to the center. Error bars indicate 95% bootstrapped CIs.

and age in months, revealed a main effect of difficulty judgments: Participants who thought that the task would be "really hard" judged that their bean bags would land, on average, farther from the target than participants who thought that the task would be "really easy" ($b = 8.75$, $p = .01$). Children's task difficulty judgments also related to their predicted learning curves. A linear mixed-effects model examining the interaction between trial and difficulty judgments on predicted performance (with random effects for participant and age) found significant interactions between trial and two levels of difficulty judgments: "kind of hard" ($b = -2.39$, $p = .01$), and "really hard" ($b = -2.68$, $p = .005$). Follow-up analyses collapsing difficulty judgments into two groups and controlling for age found that children who judged the task as "hard" predicted that their tosses would get closer to the center with repeated experience ($b = -1.36$, $p_{FDR-corrected} = .002$), whereas children who judged the task as "easy" predicted similar performance across trials ($b = -.38$, $p_{FDR-corrected} = .27$). An ordinal logistic regression predicting difficulty judgments by age also revealed that older children predicted the game was going to be harder than younger children ($b = .03$, $p = .017$): While only 44% of four-year-olds judged the task to be "kind of hard" or "really hard", a majority of five- (72%), six- (76%), seven- (70.5%) and eight-year-olds (84%) did so, respectively.

Comparison between predicted and actual performance

On average, children did not improve at the game across trials: A linear mixed-effects model predicting actual performance with trial and age and random effects for participant revealed a main effect of age ($b = -.56$, $p < .001$) and not trial ($b = -1.27$, $p = .16$). Thus, older children on average were better at the game (tossed bean bags closer to the target) than younger children, but children's performance did not improve across trials. Furthermore, there was no significant trial by age interaction on actual performance ($b = .02$, $p = .74$), showing that children's actual rate of learning did not differ by age.

We also examined whether children were accurate at predicting the shape of their own learning across trials. A linear mixed-effects model predicting actual performance as a function of predicted performance with random effects for trial, participant, and age found no effect of children's predictions on their actual performance ($b = -.08$, $p = .46$). Compared to children's actual performance, children's predicted performance was overly optimistic (average predicted toss distance $M = 13.83$, $SD = 16.29$; average actual toss distance $M = 67.22$, $SD = 36.13$; *paired* $t(124) = -21.30$, $p < .001$). Moreover, as predicted, younger children were more optimistic about their performance across trials than older children (Figure 3): A linear mixed-effects model predicting the difference between children's actual and predicted performance with trial, age, and random effects for participant revealed a significant negative effect of age ($b = -.84$, $p < .001$) and not trial ($b = -.46$, $p = .62$). Children were also more variable (higher standard deviation) in their actual performance compared to their predicted performance ($F(624) = 4.92$, $p < .001$). However, children were not sensitive to the overall variance in their performance: A linear mixed-effects model predicting participants' actual toss standard deviation as a function of their predicted standard devia-

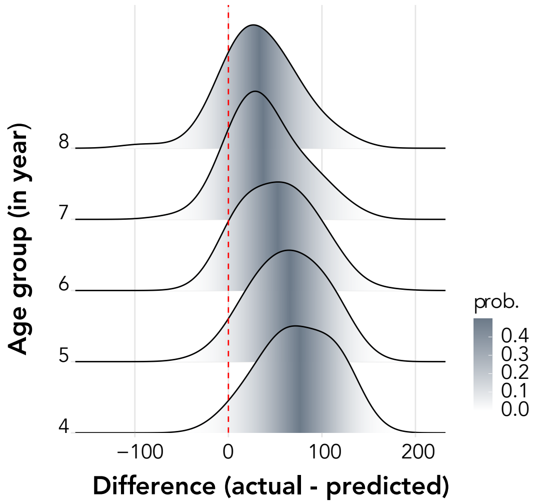

Figure 3: Density distribution of the difference between actual and predicted performance across five trials by age group. The dashed line $x = 0$ indicates a perfect match between one's actual and predicted performance, whereas values less than zero indicate underestimates, and values greater than zero indicate overestimates.

tion and random effects for age revealed no effect of predicted standard deviation ($b = .14$, $p = .31$).

Discussion

We show that by age 7, children predict that their future performance on a novel motor task will improve over time. This expectation is in line with decades of research finding that performance steadily increases throughout the first few trials of a motor task (Luft & Buitrago, 2005; Solum et al., 2020). On the other hand, 5- and 6-year-olds predicted that their performance would remain the same across trials, and 4-year-olds predicted that their performance would actually worsen over time. Consistent with prior work highlighting young children's over-optimism (Schneider, 1998), we found that younger children predicted better performance across trials and perceived the task to be easier than older children. However, in reality, younger children were worse at the motor learning task than older children.

In line with previous research (Sobel & Letourneau, 2015; Sobel, Li, & Corriveau, 2007), we found that children's representations of learning as a process develop between the ages of 4 and 8. In our work, we operationalized learning as improved performance over time and showed that children have fine-grained predictions about the shape of their learning curve. We found that by age 7, children predicted that their performance would linearly increase with practice. These predictions arose without any first-hand experience with the task, suggesting that 7- and 8-year-old children may be able to simulate the process of learning from task features alone. Our experiment was intentionally designed to support children's predictions about their performance over time: We used minimal verbal demands and made the task concrete and physical. However, despite past work showing 6-year-olds' ability to verbally describe learning using process-based responses (Sobel & Letourneau, 2015), our behavioral task revealed that 6-year-olds do not predict improved performance over time on a novel task. This may suggest that even though some children can associate concepts such as "practice" with learning by age 6, they might not yet be able to represent the learning process on a more fine-grained level or across multiple time points.

Contrary to our hypothesis, we did not find that 4- to 6-year-olds predict improvement over time. It is unclear whether younger children genuinely do not think that they will improve on novel motor tasks, or whether other factors hindered young children's performance in this context. There are a number of reasons to believe the latter. First, although we tried to reduce task demands in our paradigm, it is possible that our current experimental design was too cognitively challenging for younger children. All participants successfully restated the goal of the game, but younger children may have had difficulty remembering or prioritizing this goal when making predictions. After young children predicted "success" in the game, which they often did in their first few predictions, they may have pursued their own arbitrary goals instead of the goals imposed by the task (see Chu & Schulz, 2020; Diggs-Galligan, Chu, Tenenbaum, & Schulz, 2021). Indeed, some younger children placed all their bean bags in a straight line or in each quadrant of the target, showing a bias towards the visual features of the mat rather than the goal of the game. Young children's optimism, combined with their diminished executive functions (Best & Miller, 2010; Best, Miller, & Jones, 2009) and counterfactual reasoning (Kominsky et al., 2021; Rafetseder, Schwitalla, & Perner, 2013), may have also prevented them from predicting improvement over time. For example, 4-year-olds almost always placed their first predictions near the target's center and often thought that the game would be "really easy", showing that they either could not inhibit their desired response (Wente et al., 2020) or that their optimism blinded them from considering the necessity of practice. Our ongoing work is exploring whether alternative versions of this paradigm with lower task demands yield more sophisticated reasoning in younger children.

A strength of our paradigm is that it is relatively nonverbal, allowing us to assess how young, less-verbal children intuitively think about their future performance. However, this same strength comes with a limitation: it is difficult to infer whether children are actively applying the concept of learning per se when predicting their performance. It is possible that 7- and 8-year-olds think that their performance will improve over time, but do not associate this improvement with learning. We think that this is unlikely given prior work showing that 7- and 8-year-olds describe learning with process-based language Sobel and Letourneau (2015). It may be more likely that 4- to 5-year-olds do not think about the specific concept of learning in this task, as past work has shown that younger children verbally do not associate learning with progress Sobel and Letourneau (2015). Future work should explore specifically whether children associate task improvement with learning, as well as how they think this learning occurs (e.g., through passive or active acquisition).

Another limitation of our paradigm is that children did not actually improve on the task over the first five trials. On a range of motor tasks, adult learners often experience rapid improvement within the first few trials (Adams, 1952; Luft & Buitrago, 2005; Zhang et al., 2022). Furthermore, work by Solum et al. (2020) showed that 10-year-olds and adult participants have similar learning curves when throwing darts with their non-dominant hand. It is possible that children in our experiment were not fully focused when playing the game: They may have been distracted by the museum setting (note we tested children in an open space within the museum) or fatigued from the first part of the procedure. With more focus and effort, children may be able to improve at this task across five trials. To this end, ongoing work is testing whether children's actual performance improves across five trials when they do not first have to make predictions of their performance (thereby reducing task length before play) and are given incentives for their accurate performance to increase motivation and effort.

A future question concerns whether children predict distinct learning curves for different tasks. Generally, activities that are harder to master have flatter learning curves than tasks that are easier to learn (Gottlieb & Oudeyer, 2018; Son & Sethi, 2006). Children and adults prefer to work on tasks with steeper learning rates (Ten, Kaushik, Oudeyer, & Gottlieb, 2021; Leonard et al., 2022), suggesting that they may be sensitive to learning curves as a signal for which tasks are tractable. However, it is unknown whether children or even adults proactively predict that learning curves will differ based on task difficulty. Several parameters of learning curves may vary based on task difficulty, including starting performance, learning rate, and final performance. As such, it is unclear which feature(s) children might predict relate to task difficulty. Critically, children's predictions of these features may have downstream consequences for their actual learning, impacting which tasks they choose to pursue as well as which tasks they choose to abandon. Indeed, work in adults shows that optimistic expectations of learning help individuals persist (Geers, Wellman, & Lassiter, 2009; Solberg Nes, Evans, & Segerstrom, 2009) but hurt motivation after early setbacks, due to embarrassment (Dai, Dietvorst, Tuckfield, Milkman, & Schweitzer, 2018). Understanding both how children predict different learning curves, and how their predictions relate to their learning decisions, will help inform how we should best intervene on children's beliefs about learning.

Children's daily life is marked by learning. Here we show that children's predictions of their future learning curve change with age. Our results suggest that it is not until age 7 that children predict that their performance will improve over time. In contrast, when encountering a novel and difficult task, younger children seem to infer instant and constant success. A more comprehensive understanding of children's developing intuitions about their learning curves could help caregivers and teachers better understand their learning choices and develop interventions to help them overcome obstacles during learning.

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