Real-time processes in the development of action planning

Highlights

- We tested children's planning using eye tracking, EEG, motion tracking, and video

- Nonadaptive planners began moving before gathering perceptual information

- Adaptive planners gathered and processed perceptual information before moving

- Planning depends on improvements in a real-time perceptual-neural-motor cascade

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In brief

Using a unique combination of technologies to record perceptual, neural, and motor processes simultaneously in children, Ossmy et al. show that action planning develops through improvements in a real-time cascade—from gathering perceptual information about the task, to neural differentiation of the information, to finally executing the movement.

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Real-time processes in the development of action planning

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SUMMARY

Across species and ages, planning multi-step actions is a hallmark of intelligence and critical for survival. Traditionally, researchers adopt a "top-down" approach to action planning by focusing on the ability to create an internal representation of the world that guides the next step in a multi-step action. However, a top-down approach does not inform on underlying mechanisms, so researchers can only speculate about how and why improvements in planning occur. The current study takes a "bottom-up" approach by testing developmental changes in the real-time, moment-to-moment interplay among perceptual, neural, and motor components of action planning using simultaneous video, motion-tracking, head-mounted eye tracking, and electroencephalography (EEG). Preschoolers (n = 32) and adults (n = 22) grasped a hammer with their dominant hand to pound a peg when the hammer handle pointed in different directions. When the handle pointed toward their non-dominant hand, younger children ("nonadaptive planners") used a habitual overhand grip that interfered with wielding the hammer, whereas adults and older children ("adaptive planners") used an adaptive underhand grip. Adaptive and nonadaptive children differed in when and where they directed their gaze to obtain visual information, neural activation of the motor system before reaching, and straightness of their reach trajectories. Nonadaptive children immediately used a habitual overhand grip before gathering visual information, leaving insufficient time to form a plan before acting. Our novel bottom-up approach transcends mere speculation by providing converging evidence that the development of action planning depends on a real-time "tug of war" between habits and information gathering and processing.

INTRODUCTION

Across species and ages, action planning is a hallmark of goal-directed behavior and is critical for survival and everyday function. Actors cannot perform the same habitual actions over and over by rote because real-world environments are variable, unpredictable, and full of novel situations. Instead, for behavior to be functional, planning requires consideration of multiple possible actions while keeping the end goal in mind. Adaptive, efficient action planning is a real-time, moment-to-moment process involving integration among perceptual, cognitive, and motor systems as actors gather and process information about the environment and use it to control their movements.[1] However, little is known about the underlying processes or what happens to motor control when information gathering or processing goes awry.

For some actions, visual information for the end goal is available in the scene (e.g., grasping an object). In humans, using such readily available information to achieve a goal begins in infancy.[2–4] With age and experience, actions become more *adaptive* (the most appropriate action is selected to achieve the goal) and *efficient* (movements are fast, smooth, and accurate). For example, human infants show developmental improvements in shaping their hand and controlling their reach trajectory to grasp objects varying in size and orientation.[5,6]

However, many everyday actions involve multiple steps so that the end goal stretches far into the future. Thus, visual information for the initial action is present in the scene, but information for the final action is not. Rather, the final action must be constructed mentally in anticipation of the future, unseen end goal.[1,7] And sometimes the initial action requires nonhabitual—even uncomfortable—movements to ensure that the final action is best suited to achieve the end goal.

Consider multi-step tool use; when adults want to hammer a peg and the handle points toward their non-dominant hand, they plan two steps ahead by grasping the hammer with an adaptive, nonhabitual, underhand grip that allows for a smooth, efficient transition to a comfortable, overhand grip to pound the peg (Figure 1A, top row).[8] In contrast to adults, when children grasp the handle of a hammer, they rely on their habitual overhand grip (Figure 1A, bottom row).[8] Thus, when the handle points away from their dominant hand, children find themselves in an awkward, maladaptive position to pound the peg (with their pinky finger closer to the hammer head in an ulnar grip). They must resort to clumsy and inefficient online error corrections to accomplish the end goal (e.g., putting the hammer down to swap grips). More generally, in multi-step actions involving tools such as hammers and spoons and in multi-step actions that involve turning handles, rotating dowels, or flipping upside-down water glasses,
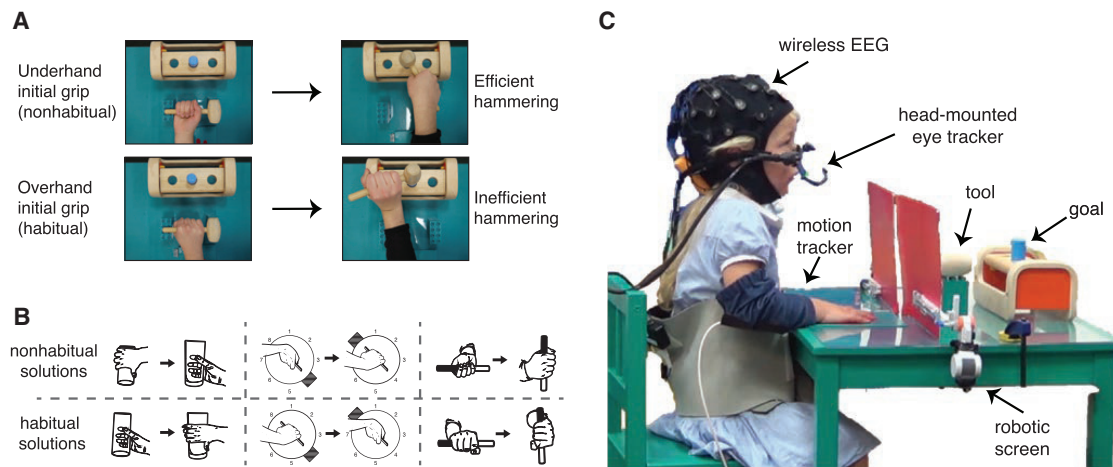
Figure 1. Grip configurations and experimental setup

(A) Hammering task when handle of hammer points away from the dominant hand ("nonhabitual" trials). Initial grips and subsequent hand position for hammering. Top: nonhabitual, underhand/radial grip leads to a comfortable position for pounding the peg. Bottom: habitual, overhand/ulnar grip leads to an awkward position for pounding the peg.

(B) Nonhabitual (top panel) versus habitual (bottom panel) solutions to various multi-step actions. Drawings show hand configurations for initial grip (left of arrows) and subsequent manipulation of the object (right of arrows). Examples of nonhabitual action: an initial thumb-down grip allows for optimal thumb-up grip while filling the glass; a highly torqued initial grip allows for optimal end grip while turning the handle; and an initial underhand grip allows for optimal thumb-up grip while placing the dowel. The habitual solutions are not adaptive—initial thumb-up grip leads to awkward thumb-down grip while filling the glass; minimally torqued initial grip leads to a highly torqued and awkward grip while turning the handle; and initial overhand grip leads to awkward thumb-down grip while placing the dowel.

(C) Experimental setup in hammer-and-peg task. Participants sat in front of a robotic screen and were asked to wield a toy hammer to pound a peg. They wore a head-mounted eye tracker, EEG cap, and motion-tracking sleeve and their reach and grasp actions were recorded on video.

infants and young children rely on habitual initial actions and thus fail to perform the final actions in adaptive and efficient ways (Figure 1B).[8,9] Children show developmental improvements in such multi-step actions until about 10–12 years of age, when most attain adult-like levels of performance.[2,10–12]

Nonhuman primates also show developmental improvements in multi-step planning. For example, when wild bearded capuchin monkeys use a stick as a tool to obtain food out of reach, young monkeys use a habitual, awkward ulnar grip that makes it difficult to wield the tool. With age, monkeys shift to a nonhabitual, more efficient radial grip that brings the food more easily within reach.[13]

Tool use is an important paradigm for the study of multi-step action planning because successful implementation always reflects planning for a distant goal. Traditionally, researchers adopt a "top-down" explanation of evolutionary and developmental changes in planning during tool use.[8,14–16] They argue that improvements in tool use—and therefore in planning—reflect the ability to form internal representational models of task contingencies to evaluate possible actions and predict the optimal initial action. More generally, this top-down approach is the foundation of most research on planning in psychology and neuroscience.[16,17]

However, as suggested by the embodied theory of tool use in children and nonhuman primates,[18,19] a "top-down" perspective relies on the functionality of the tool and the outcome of implementation but does not account for changes in biomechanics, body-environment relations, or perception-action coupling. The top-down approach focuses on *what* is planned, but not on *how* planning occurs from moment to moment. Thus,

although researchers from both the traditional and embodied perspectives agree that the way the tool is grasped reflects planning or lack thereof,[1,10,19] proponents of both perspectives can only speculate about the mechanisms underlying how and why developmental improvements in planning occur. Relying solely on observable movements to inform on inner representational models leads to speculative arguments because planning involves processes that are not captured in observable motor actions such as grip configuration. Planning involves a real-time cascade of perceptual, neural, and motor events.[20,21] The cascade begins with gathering task-relevant visual information; this information is then neurally integrated with the motor system; and finally the action is produced.

Moreover, in adults, the real-time planning cascade is extremely fast and efficient. In less than 4 s, adults detect the hammer orientation, reach for the hammer, grasp the hammer adaptively, and pound the peg.[8] In such a rapid cascade, processes must be precisely timed and sequenced. However, previous research focused only on improvements in planning over large timescales—how infants and children become better planners over development[22,23] or how planning changes across trials within a session.[8,24] No previous work described the unfolding of the real-time planning cascade *within a trial*, from moment to moment. Thus, despite the importance of action planning in developmental and cross-species research, prior work could not address how differences in planning at a timescale of milliseconds—the timescale when action plans are formed and implemented—relates to improvements in multi-step actions.

Here, we analyzed action planning as children and adults grasped a hammer to pound a peg. We varied the orientation
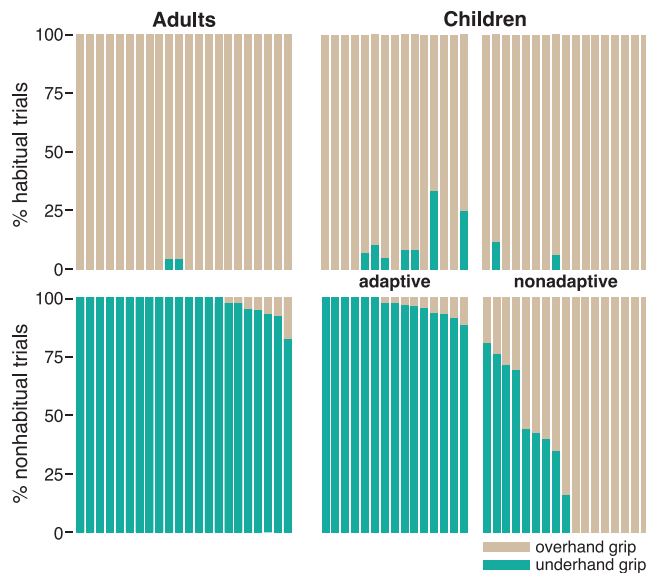
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Figure 2. Primary measure of adaptive multi-step action
Inter- and intraindividual variability in initial grip on habitual (top) and nonhabitual trials (bottom). In the nonhabitual trials, adults and 15 children (adaptive child planners) used underhand grips (>82.5% of nonhabitual trials), and 17 nonadaptive child planners were more variable or continued to use the habitual, overhand grip regardless of handle direction. Each pair of vertical bars represents a single participant in the habitual and nonhabitual trials. For differences in duration and implementation error, see Figure S1.

of the hammer to manipulate whether a habitual overhand grip or nonhabitual underhand grip was more adaptive and to assess orientation-based differences in the planning cascade (Figure 1A). In other words, we used hammering as a model system to investigate planning of goal-directed actions in a situation that requires actors to "represent" the position of the hand for the end-goal because the visual information for final hand position is not available in the initial scene.

We assessed action *adaptiveness* based on participants' initial grip on the hammer. On "habitual" trials, the handle of the hammer pointed toward participants' dominant hand; therefore, adaptive planning would be evidenced by a habitual, overhand grip. On "nonhabitual" trials, the handle pointed toward participants' non-dominant hand; thus, adaptive planning would be evidenced by a nonhabitual, underhand grip (Figure 1A, top row). Differences in grip configuration between the two conditions would indicate that participants used information about hammer orientation to plan for the unseen end goal. We assessed action *efficiency* based on how quickly and smoothly participants grasped the hammer and whether their pounding was accurate (hit or missed the peg).

We diverged from the traditional formalism based on covert, inner representations that predict action outcomes. Instead, we considered planning as a real-time cascade based on a combination of interdisciplinary perspectives and methods from developmental psychology, neuroscience, and movement science. We used a unique combination of simultaneous technologies to test the real-time planning cascade. Participants wore a head-mounted eye tracker to record where they looked and when, an electroencephalography (EEG) cap to measure their neural

activity during planning, and a motion tracker to record the otherwise unobservable details of their hand trajectory (Figure 1C). Video captured their initial grasp and success at pounding the peg. We recorded moment-to-moment processes in perceptual, neural, and motoric components of action planning as participants grasped the hammer. We tested children at an age (3 to 5 years) when they were sure to succeed in using the hammer to pound the peg—regardless of whether they did so adaptively and efficiently—but potentially lack adult-like, multi-step planning.

Our novel, simultaneous recording methods provide new insights into the typically hidden perceptual, neural, and motoric processes that underlie multi-step action planning. Based on previous work,[8] we expected actions to become more adaptive and efficient with children's age, and from children to adults. Thus, our primary hypothesis was that age-related differences in adaptive, efficient tool use depend on developmental changes in the timing of each component in the real-time planning cascade. We predicted that adaptive child planners at every age would plan solutions ahead of time by starting the cascade early and maintaining the correct order of components (early fixation to the hammer, neural differentiation of handle direction, and then movement onset). In contrast, nonadaptive child planners would rely on habitual overhand grips on nonhabitual trials (Figure 1A, bottom row) and resort to online error correction because they started the cascade too late and began moving their hand before gathering and processing the requisite information. Moreover, we predicted that adult-like planning would lead to smoother, more direct reaching trajectories in both the habitual and nonhabitual conditions.

RESULTS

Participants contributed $M = 58.20$ trials (21.14 habitual trials, 37.05 nonhabitual trials). Adults and children did not differ in the total number of trials, $Ms = 60.18$ (SD = 0.50) and 56.84 (SD = 14.93) respectively; $t(52) = 1.04$, p = 0.30. Preliminary analyses showed no effects of gender, so it was collapsed in subsequent analyses.

Planning became more adaptive and efficient with development

All participants were highly motivated by the hammering task and pounded the peg flat on every trial. However, children were less *adaptive* than adults. On habitual trials, both age groups used the habitual overhand grip, but adults tended to be more consistent than children, $Ms = 99.60\%$ and 96.40% respectively, $t(52) = 1.93$, p = 0.06 (Figure 2, top panel). On nonhabitual trials, adults uniformly used initial underhand grips, $M = 97.72\%$, SD = 4.21 (Figure 2, left-bottom panel), whereas children's grip choices were variable, $M = 60.12\%$, SD = 41.57 (Figure 2, right-bottom panel). Overall, adults performed more underhand grips than children on nonhabitual trials, $t(52) = 4.21$, p < 0.01. In children, the proportion of underhand grips increased with age, $r(30) = 0.50$, p < 0.01 (Spearman correlation).

Children were also less *efficient* than adults on nonhabitual trials. Children were slower to pound the peg flat compared to adults, $Ms = 6.61$ s (SD = 2.16) and 2.66 s (SD = 0.88), respectively, from the moment the trial started, $t(52) = 8.09$, p < 0.01 (Figure S1A). And children were less accurate (i.e., were more
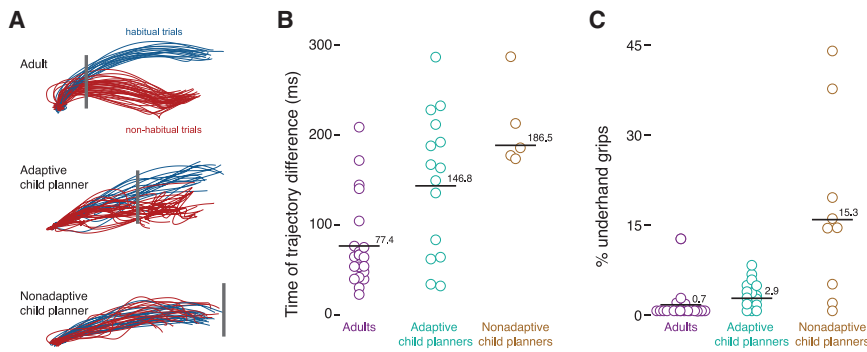
Figure 3. Measures of efficiency and early planning in adults, adaptive child planners, and nonadaptive child planners

(A) Motion-tracking shows reach trajectories for each trial in exemplar participant from each group. Adult exemplar shows more efficient (smoother, more consistent) reach trajectories than child exemplars. Moreover, the adult and adaptive child planner showed differentiation in reach trajectories between habitual and non-habitual trials, whereas the nonadaptive child planner showed identical reach trajectories for both hammer-orientation conditions. Vertical lines indicate the moment of significant trajectory difference between conditions (line to right of nonadaptive child planner denotes no trajectory difference before grasping). Note that the figure shows only the spatial shape of the reach and not its duration.

(B) Time to differentiate reach trajectories between habitual and nonhabitual trials. Time is relative to movement onset (the beginning of the reach). Symbols denote the mean differentiation time for each participant. Horizontal lines denote group means. Adults showed earlier differentiation of reach trajectories, followed by adaptive child planners, and finally nonadaptive child planners. Most nonadaptive child planners (12 of 17) did not show trajectory difference.

(C) Last-moment decisions (an index of inefficiency) to use underhand grips on nonhabitual trials. Nonadaptive child planners showed more last-moment decisions (See STAR Methods). Note, only 9 nonadaptive child planners used an underhand grip.

See also Figure S2.

likely to miss the peg; see Database: databrary.org/volume/434/slot/51705), Ms = 7.71 (SD = 4.28) and 0.63 (SD = 0.84) errors per session, respectively, $t(52)$ = 7.63, p < 0.01 (Figure S1B). Moreover, children's efficiency depended on how they first grasped the hammer. We found a significant negative correlation between the proportion of underhand grips and trial duration, $r(30)$ = −.49, p < 0.01, and between the proportion of underhand grips and the number of misses, $r(30)$ = −.55, p < 0.01. Thus, when children used an underhand grip on nonhabitual trials, they were faster and more accurate compared to when they used an overhand grip. When children did use an overhand grip, speed and accuracy depended on whether they changed their grip after the initial grasp of the hammer. Children changed their initial overhand grips on 79.88% of the nonhabitual trials. They were slower when they changed their grip compared to when they pounded the peg with an awkward grip, Ms = 7.87 s (SD = 4.21) and 6.94 s (SD = 3.43), respectively, $t(505)$ = 2.06, p < 0.04. But after changing grips, they tended to be more accurate (see STAR Methods) than when they did not, Ms = 0.27 (SD = 0.46) and 0.26 (SD = 0.44) implementation errors, respectively, $t(505)$ = 1.12, p < 0.07.

Figure 2 and Figure S1 show that interindividual variability in the adaptiveness of participants' planning and efficiency of their actions was higher in children than adults. To understand the sources of individual differences, we split children into two groups based on their initial grips. One group—adaptive child planners—included all children who demonstrated adult-like planning (n = 15). That is, they used the underhand grip on at least 82.50% of the nonhabitual trials (this criterion was determined by the minimum percent of underhand grips in adults) (Figure 2, bottom panel). The second group—nonadaptive child planners—included the other children (n = 17). Our subsequent analyses focused on differences in planning between adults and adaptive and nonadaptive child planners.

Importantly, group differences did not result from within-session learning. Children did not show evidence of learning across trials. That is, children were not more adaptive or more efficient in later trials compared to early ones. We examined learning effects

by comparing performance across trial blocks of nonhabitual trials. One-way ANOVAs on the number of underhand grips, $F(3,111)$ < 0.42, p > 0.73, hammering speed, $F(3,11)$ < 1.86, p > 0.14, and hammering accuracy, $F(3,111)$ < 0.27, p > 0.84, confirmed no within-session learning.

Adaptive actors plan ahead

Early differences in reach trajectories for habitual versus nonhabitual trials indicate more planning ahead than differences at the last moment before grasping the hammer (or not at all). Adults, adaptive child planners, and nonadaptive child planners differed in when they planned their reach trajectory. Figure 3A shows the reach trajectories of one exemplar participant per group. The adult showed smoother movements and earlier differentiation of reach trajectories between habitual and nonhabitual trials compared with the children, and the adaptive child planner showed earlier differentiation compared with the nonadaptive child. Across the sample, we determined the trajectory difference as a significant difference in the average distance between each pair of trials within the same condition versus each pair of trials across different conditions (Figure S2). We found an earlier difference in the reach trajectory in adults compared with children, and in the reach trajectory in adaptive child planners compared with nonadaptive child planners (see STAR Methods and Figure S2). A one-way ANOVA on the time to differentiate reach trajectories (see STAR Methods) confirmed effects at the group level: Ms = 77.42 ms, 146.86 ms, and 186.55 ms after movement onset for adults, adaptive child planners, and nonadaptive child planners, respectively, $F(2,53)$ = 13.20, p < 0.01 (Figure 3B). For the nonadaptive child planners, trajectory differentiation occurred after the moment of the initial grasp, so their reaches showed no differentiation in trajectories. Sidak-corrected post hoc comparisons confirmed significant differences between each pair of groups, all ps < 0.01.

We also found differences in how participants planned underhand grips on nonhabitual trials. We identified trials in which participants made last-moment grip decisions (i.e., began to reach and then changed direction to accommodate a switch from
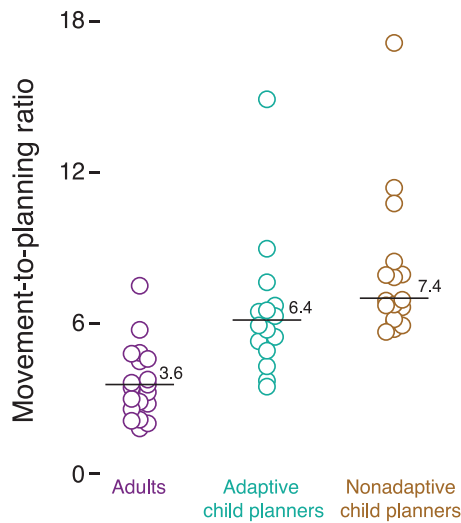
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Figure 4. Movement-to-planning ratios in adults, adaptive child planners, and nonadaptive child planners

Symbols denote the mean ratio for each participant (movement time divided by reaction time). Horizontal lines denote group means. Adults showed lower ratios (i.e., they spent relatively more time planning and less time moving), followed by adaptive child planners, and finally nonadaptive child planners. The analysis includes habitual and nonhabitual trials.
See also Figure S3.

overhand to underhand); see Database: databrary.org/volume/434/slot/51706. On the few trials when nonadaptive child planners used an underhand grip, they did so at the last moment (see Video Coding in STAR Methods) more often ($M = 15.33\%$ of underhand grips) than adaptive child planners, $M = 2.90\%$. Adults showed even fewer last-moment decisions, $M = 0.69\%$, $F(2, 43) = 11.56$, p < 0.01 (Figure 3C). Sidak-corrected post hoc comparisons confirmed significant differences between nonadaptive child planners and the other two groups, ps < 0.01.

Finally, the timing when participants lifted their hand to reach—relative to when the screen raised and the handle direction was revealed—was related to adaptive versus nonadaptive initial grips. Across all trials (habitual and nonhabitual), the ratio between participants' movement time (beginning of reach to moment when the hammer touched the peg; $M = 3.90$ s, SD = 2.21 across all participants) and their planning time (from screen raise to beginning of reach; $M = 0.90$ s, SD = 0.41 across all participants) (see STAR Methods and Figure S3) reflects whether they began moving before or after forming a plan. A low ratio means that participants invested time in planning before starting to reach. Across all participants, the movement-to-planning ratio ranged from 1.41 to 27.41. As shown in Figure 4, adults had the lowest movement-to-planning ratio, $M = 3.65$, SD = 1.36, and adaptive child planners had a lower ratio than nonadaptive child planners (Ms = 6.42 and 7.40, respectively). A one-way ANOVA on the movement-to-planning ratio confirmed a group effect, $F(2, 53) = 12.73$, p < 0.01; post hocs confirmed differences between all three groups, all ps < 0.05.

Planning ahead depends on the real-time interplay between planning components

Early, focused, and sustained visual attention to the hammer and neural processing of the perceptual information—all before

moving the hand to reach—were critical for adaptive action planning. From the moment the direction of the hammer was revealed, adults directed their gaze to the hammer earlier, $M = 336.73$ ms, SD = 138.47, than did adaptive child planners, $M = 628.13$ ms, SD = 142.70, who in turn were earlier than nonadaptive child planners, $M = 839.73$ ms, SD = 196.68. A one-way ANOVA confirmed a main effect for group, $F(2, 53) = 48.45$, p < 0.01; post hocs confirmed differences between all three groups, all ps < 0.05 (Figure 5A).

Moreover, focused attention was critical for adaptive planning (Figure 5B). Adults mainly fixated the hammer ($M = 43.23\%$ of the time interval between screen opening to reach onset, SD = 20.05) rather than the peg ($M = 13.43\%$, SD = 14.91) or their hand ($M = 0.88\%$, SD = 1.51). Adaptive child planners showed a similar pattern, but to a lesser extent ($M = 25.88\%$, SD = 13.75 on hammer; $M = 8.05\%$, SD = 3.66 on peg; $M = 3.68\%$, SD = 2.99 on hand), whereas nonadaptive child planners spread fixations equally across areas of interest ($M = 14.03\%$, SD = 6.55 on hammer; $M = 12.45\%$, SD = 8.29 on peg; $M = 10.11\%$, SD = 6.06 on hand). A 3 (groups) × 3 (areas of interest) mixed model ANOVA confirmed main effects for group $F(2, 51) = 12.47$, p < 0.01, and area $F(1, 51) = 27.70$, p < 0.01, and an interaction between group and area $F(2, 51) = 7.47$, p < 0.01. Sidak-corrected post hoc tests confirmed higher percentages in looking at the hammer in adults than adaptive child planners and higher percentages in adaptive child planners than nonadaptive child planners, all ps < 0.05, and no group differences in looking at the hand or the peg, all ps > 0.05 (Figure 5B).

In addition, sustaining attention to the hammer supported adaptive planning (heatmaps in Figure 5D). Adults looked at $M = 9.27\%$ of pixels in the video frames in each trial, adaptive child planners looked at $M = 15.81\%$ of the pixels, and nonadaptive child planners looked at $M = 20.85\%$ (see Database: databrary.org/volume/434/slot/51707). A one-way ANOVA confirmed a main effect for group, $F(2, 51) = 37.05$, p < 0.01. Sidak-corrected post hoc tests showed broader distribution of attention (see STAR Methods) in nonadaptive child planners compared to the other two groups, all ps < 0.05 (Figure 5C).

Finally, neural processing of the handle direction before reach onset was critical for adaptive planning. Because nonhabitual trials required a different action plan than habitual trials, we analyzed differences between conditions in readiness potential—event-related potential over the sensorimotor cortex preceding movement known to correspond to motor planning (see STAR Methods). Figure 6 shows that readiness potentials in adults significantly differed between conditions at $M = 417.63$ ms, SD = 99.39 before reach onset. Adaptive child planners showed significant neural differentiation later, at $M = 242.78$ ms, SD = 69.00 before reach onset. But readiness potential in nonadaptive child planners did not differ between conditions. Overall, readiness potential did not differ between left- and right-handed participants.

DISCUSSION

Prior work showed that multi-step action planning improves over evolution and development.[8,10,25,26] For example, previous researchers showed that adults are more adaptive than children, older children are more adaptive than younger children, and
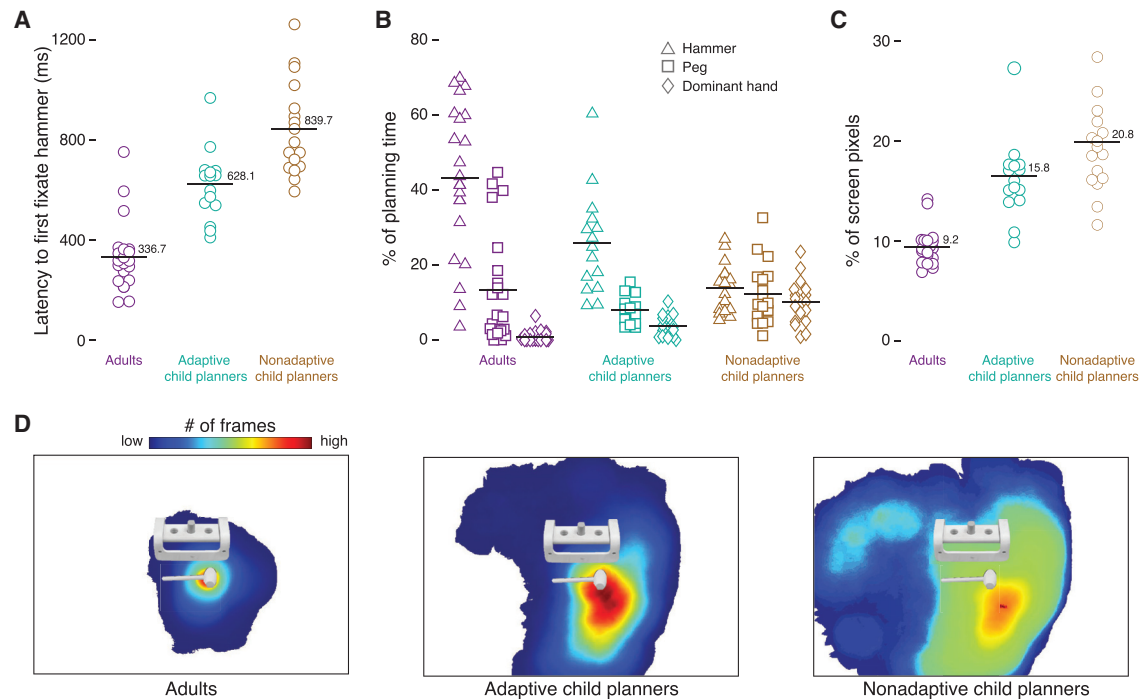
Figure 5. Visual information gathering prior to moving the hand in adults, adaptive child planners, and nonadaptive child planners

(A) Latency to fixate the hammer after the screen lifted. Symbols denote the mean latency for each participant. Horizontal lines denote group means. Adults showed smaller latencies, followed by adaptive child planners, and finally nonadaptive child planners.

(B) Looking to ROIs (hammer, peg board, dominant hand) during the period from screen opening to moving the hand (i.e., percent of planning time). Symbols denote the mean percent of planning time for each participant. Horizontal lines denote group means. Adults and adaptive child planners looked more at the hammer than at the peg or their hand compared with nonadaptive child planners.

(C) Percent of pixels fixated during the period from screen opening to moving the hand. Smaller percentages indicate more focused attention. Symbols denote the mean percent of pixels for each participant. Horizontal lines denote group means. Adults focused visual attention on a smaller number of pixels compared with adaptive child planners, followed by nonadaptive child planners.

(D) Heatmaps showing dispersion of visual attention accumulated across each group. Colored regions denote areas fixated. Hotter colors denote longer accumulated fixation times. Adults focused visual attention on a smaller region of space (surrounding the hammer) compared with adaptive child planners (whose visual attention included the peg board and surrounds), followed by nonadaptive child planners. Note heatmaps in (D) cover more area than individual data in (C) because often participants' fixation locations did not overlap.

nonadaptive children show rampant intra- and interindividual variability.[8,11] We did likewise.

However, prior work could only speculate about the causes of children's nonadaptive, inefficient performance. Here, we used a novel combination of simultaneous recording methods—head-mounted eye tracking, EEG, motion tracking, and third-person video—to transcend mere speculation. We identified the real-time, within-trial factors that underlie developmental improvements in planning. As we predicted, more adult-like planning led to more adaptive and efficient performance. And as we hypothesized, adults and adaptive child planners were adaptive and efficient because they started the real-time planning cascade early and maintained the correct order of planning components. As summarized in Figure 7, adaptive planners gathered and processed perceptual information *before* they began moving; that is, they displayed early visual fixation to the hammer and early neural differentiation of the motor plan. As a consequence, adaptive planners showed early movement differentiation between overhand and underhand grips. In contrast, nonadaptive child planners started the cascade too late and thus displayed later components of the cascade (e.g., began to reach) before earlier

ones (e.g., gathered visual information) or failed to display all the components (i.e., failed to differentiate perceptual information via neural activity or reach trajectories). As shown by the planning cascades for each participant in Figure S4, planning in nonadaptive planners went awry from the first reveal of the tool, and errors consequently propagated through the system.

A developmental tug of war between habits and early information gathering

We suggest that adaptive, efficient planning emerges from developmental improvements in a real-time "tug of war" between habits and information gathering and processing. All things being equal, children and adults rely on habitual actions that compete with new information. Thus, early gathering and processing of perceptual information about task constraints provided adults and adaptive child planners with sufficient time to determine whether the habitual overhand grip was appropriate for the specific situation (i.e., direction of hammer). On nonhabitual trials, it gave them time to determine that the habitual grip was not optimal and a nonhabitual—initially awkward—underhand grip offered more adaptive and efficient tool implementation. Thus, *adaptive*
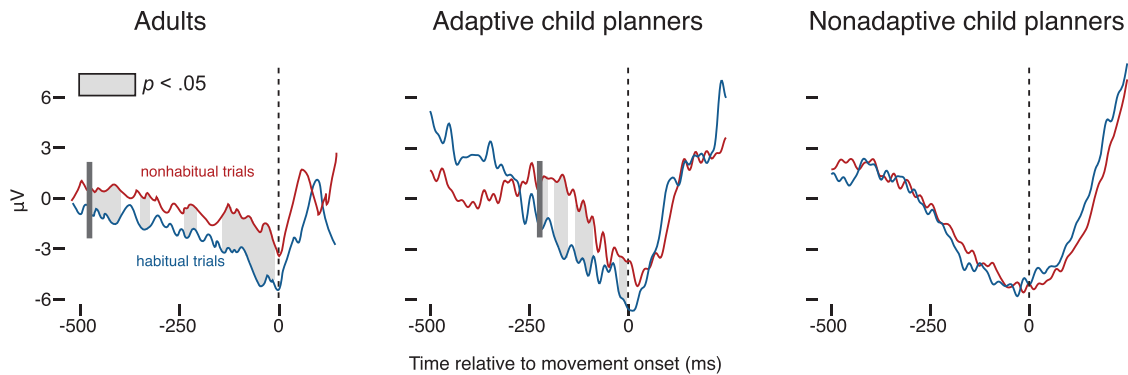
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Figure 6. Neural differentiation (EEG) prior to moving the hand

Average readiness potential in habitual and nonhabitual conditions in adults, adaptive child planners, and nonadaptive child planners. Light-gray regions denote significant differences between conditions (ps < .05). Vertical dark-gray lines denote the average onset of neural differentiation. Vertical dashed lines denote the moment of movement onset. Adults showed earlier neural differentiation compared with adaptive child planners, and nonadaptive child planners did not show any neural differentiation prior to movement onset. As in Figure 3, time is relative to movement onset (the beginning of the reach).

planners generated a plan in the moment. They could do so because they looked at the task-relevant areas early enough to discover the task demands and give their brains sufficient time to process the perceptual information and to form a plan before acting. In contrast, nonadaptive child planners were slow to gather task-relevant information, leaving insufficient time to process the information in their brains before movement onset. This led nonadaptive planners to rely on their habitual action and resort to online error correction.

The real-time tug of war was further supported by the EEG results. The early phase of neural activity in the motor cortex prior to movement, captured by the readiness potential, is believed to be associated with preparation and initiation of the forthcoming motor act.[27–29] A difference in readiness potential between habitual and nonhabitual trials indicates that "neural commands" from the motor cortex to the effectors differed between the conditions. The timing of a significant difference reflects *when* these commands began to differ. An earlier difference indicates early processing of the visual information and its translation to muscle activity. We argue that adults and adaptive child planners integrated visual information about the hammer in their neural commands, but less visual information was integrated in nonadaptive planners because it was not sufficiently gathered. Thus, the timing of the readiness-potential difference between adults, adaptive child planners, and nonadaptive child planners suggests that developmental changes in neural processing play a role in driving developmental changes in multi-step planning. Future research should investigate the readiness-potential difference itself and not just its timing—that is, why the readiness potential was lower in habitual compared to nonhabitual trials. This result is somewhat counterintuitive (nonhabitual trials require more complex planning than habitual trials), yet consistent across groups (the direction of the difference was the same in adults and adaptive planners although the timing differed). We could not address this question in the current study because it requires identification of neural patterns that are based on hundreds of trials per participant and collecting such data was not feasible with children.

Another aspect of the real-time tug of war concerns executive functioning, specifically, participants' inhibitory control. Recent studies demonstrated the importance of inhibitory control in real-time motor problem solving and action planning.[30] Preschoolers improved in solving motor problems ahead of time by developing the ability to inhibit habitual actions and select more appropriate actions. We suggest that the development of inhibitory skills allows children to "gain" sufficient time to gather and process information that leads to better multi-step planning.

The real-time tug of war during action planning aligns with computational cognitive research that distinguishes between model-free and model-based decision-making strategies.[16,31] With a model-free strategy, agents repeat actions that were frequently rewarded in the past. With a model-based strategy, agents acquire an internal representation of the task to evaluate possible actions. Previous research revealed model-free decision-making strategies in both children and adults, whereas a model-based strategy emerges only in adolescence and increases with age.[32] Similarly, we found that nonadaptive child planners repeated a habitual overhand grip that presumably worked for them in most everyday grasping tasks (akin to a model-free strategy), whereas adults and adaptive child planners learned to initiate an early planning cascade so they could evaluate possible actions rather than simply execute the habitual one (akin to a model-based strategy). Our findings suggest that a developmental shift from a model-free to a model-based strategy is not only relevant for higher-level cognition such as decision making, cognitive flexibility, executive function, and self-regulation. It is also critical for action planning, and the shift depends on the age when children learn the optimal time to gather and process perceptual information. In some cases, adults formed a neural plan *while* gathering information, indicating a model-based process of "pulling out" an existing plan at the first sight of the hammer in the periphery of their visual field (there was only one such case in children). Further research on the connections between perceptual-motor planning and computational cognitive research is required to address the gap between action planning and higher cognitive functions.

Planning to plan: The role of perception in early action planning

Ours is not the first study, of course, to investigate action planning and its relations to habitual actions. Most empirical and
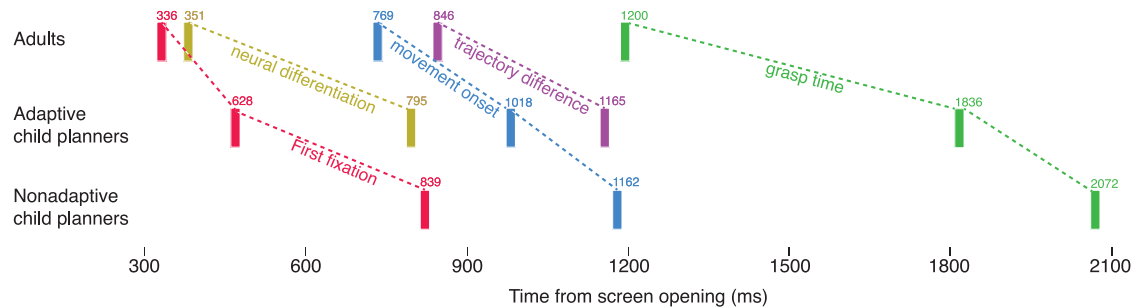
Figure 7. Timing of the real-time planning cascade
The cascade started when the screen opened and ended at grasp of the hammer handle. Vertical solid lines denote group averages for each component. Dashed lines facilitate comparisons between groups. Adults displayed earlier visual fixation to the hammer, earlier neural differentiation of the handle orientation, earlier movement onset, and earlier differentiation of reach trajectories than adaptive child planners. The adaptive child planners, in turn, displayed more components of the cascade and earlier registration of displayed components than nonadaptive child planners. Note that all time points are relative to the screen opening (unlike Figure 3 and Figure 6 where time points are relative to movement onset).
See Figure S4 for the timing of the real-time planning cascade in individual participants.

computational work argues that actors acquire the ability to plan ahead when they learn to maintain a cognitive representation of future action consequences based on the initial task parameters.[33,34] In other words, actors learn to plan their actions prior to commencing a movement when they learn to anticipate the outcome of a specific action given the environmental characteristics and requirements with which the action is being performed.

However, traditionally researchers focus on covert, representational models and pay little attention to the way perceptual information is gathered and processed and how it supports action planning. But what is the direct behavioral and neurophysiological evidence that planners (humans or other animals) rely on gathering and processing information from the environment? In prior work, information about task parameters was taken for granted, as if the environment were already known before movement commenced.[35,36] By investigating the typically hidden perceptual, neural, and motor processes that underlie planning from moment to moment, we show this is not the case. Participants did not simply "know" all the relevant information about the hammering task before the screen lifted at the start of each trial. How could they? They needed to deliberately point their eyes to the visual information that would allow them to plan their actions. Children's deficit in planning ahead results from deficits in "planning to plan." Looking is itself a motor action that requires planning,[37] and nonadaptive child planners did not plan when and where to look. This finding expands on prior work showing that adults plan their actions better than children during object fitting because adults gather information about the object and aperture earlier than do children.[20]

Moreover, passive feedback about action consequences does not necessarily improve children's planning. For example, when performing multi-step actions such as flipping a dowel or an overturned water glass (Figure 1B), feedback about the consequence of the movement (flashing lights) did not improve children's motor planning.[38] Apparently, planning to plan must be instigated by the actor.

Finally, research with nonhuman primates shows that multi-step action planning is not limited to the selection of the appropriate action at the appropriate time. Action planning also involves matching the appropriate means to the selected action. For example, wild capuchin monkeys consistently select heavier stones to crack nuts,[39] wild chimpanzees select hammers in accord with the resistance of the nut they want to crack,[14] and long-tailed macaques use differently shaped stones for scraping and hammering.[40] Future research should explore how evolutionary and developmental improvements in selecting means are affected by changes in planning to plan.

The value of a real-time approach to the development of planning
Typical research practices limit theoretical conclusions about the development of planning. In most studies, each child receives only one trial or perhaps a few trials; thus planning must be assessed based on the percent of children at each age who show efficient versus inefficient planning.[11] However, small numbers of trials and group averages provide little information about the causes of intra- and interindividual variability. Intraindividual variability was evident in more than half of the child planners (Figure 2) and likewise was rampant in previous work,[8,23] in which adults consistently used the efficient underhand grip.

Moreover, researchers typically evaluate planning efficiency based on the outcome of selected actions[41] or use reaction time (the time for actors to start moving) as a proxy for unspecified processes that occur before movement begins.[42] However, a focus only on movement outcomes limits potential explanatory mechanisms. For example, Rosenbaum and Feghhi[41] argue that children gradually adopt more adult-like planning because their joints become stiffer as they mature, which reduces the number of movement strategies and makes the most efficient strategy more obvious. Biomechanical changes may indeed be important in the development of planning, but other factors are also likely contributors. Although reaction time reflects processes prior to movement, shorter reaction times do not indicate *which processes* improved in planning.[21]

Our multi-method approach demonstrates the promise of measuring the real-time interplay among perceptual, neural, and motor processes during planning over many trials for each child, before and after movement onset (as shown in Figure S4). We obtained 60 trials per child, used a novel combination of real-time recording technologies, and examined planning processes

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prior to movement (gaze locations, neural differentiation of readiness potential) and after reach onset (differentiation of reach trajectories and grip choices). Our findings pave the way for research on the causes of nonadaptive, inefficient planning in individual children. Some children may fail to gather the relevant perceptual information before acting. As Ossmy and colleagues[20] put it, they "leap before they look." Other children may fail to process the information rapidly and adequately. In other words, the problem is not a lack of perceptual information but rather what children do with the information they obtain.[43] And even when children obtain the relevant information before performing the action, and process it quickly and appropriately, they trail behind adults because they lack adult-like motor dexterity.[41] One component of the planning cascade can affect downstream components, and some children may suffer from deficits on all counts. Testing these failures at the individual level may have translational implications for understanding disorders related to deficits in action planning and thereby support interventions to foster planning in individual children. Presumably, by knowing the source of deficits in individuals, interventions can be tailored to people's specific needs.

Conclusions

We investigated deficits in children's action planning by examining the moment-to-moment interplay among planning components. In contrast to the traditional formalism of planning that relies on a covert, inner representation of the world, we considered planning as a real-time cascade of perceptual, neural, and motor processes. Our uniquely powerful combination of head-mounted eye tracking, EEG, motion tacking, and video indicates that each component of the real-time planning cascade contributes to planning efficiency. And developmental changes in planning are driven by changes in the onset of the planning cascade and the timing of its components. Our findings provide new insights into the role of perception in action planning and suggest that adaptive and efficient planning depends on a temporal competition between habitual motor actions and the gathering and processing of perceptual information. Our data, recording methods, and multivariate analytic techniques may pave the way for psychologists, animal researchers, computer scientists, and roboticists to understand planning and problem-solving processes, and for clinicians and parents to promote children's function.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

- KEY RESOURCES TABLE
- RESOURCE AVAILABILITY
  - Lead contact
  - Materials availability
  - Data and code availability
- EXPERIMENTAL MODEL AND SUBJECT DETAILS
  - Participants
- METHOD DETAILS
  - Procedure
  - Recording Devices
  - Video Coding

- QUANTIFICATION AND STATISTICAL ANALYSIS
  - Motion tracking: Data Processing and Analysis
  - Eye tracking: Heatmaps and Distribution of Attention
  - EEG: Data Processing and Analysis

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.cub.2021.11.018.

AUTHOR CONTRIBUTIONS

O.O. and K.E.A. developed the study concept, design, and interpretation. O.O., B.K., D.H., M.X., and C.B. collected the data. O.O., B.K., D.H., M.X., and C.B. coded the videos. O.O. developed and performed other analyses. O.O. and K.E.A. wrote the manuscript and all authors approved the final version of the manuscript for submission.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited Data		
Third-person videos	This paper	https://nyu.databrary.org/volume/434
Software and Algorithms		
Data coding software	Datavyu	https://datavyu.org/

RESOURCE AVAILABILITY

Lead contact
Requests for further information and data resources should be directed to and will be fulfilled by the Lead Contact, Karen Adolph (karen.adolph@nyu.edu).

Materials availability
This study did not generate new reagents.

Data and code availability
Non-identifiable data (motion tracking and EEG) are publicly shared in Databrary web-based library (Database:databrary.org/volume/434). With participants' permission, their identifiable videos, demographic data, and coding spreadsheets are shared in Databrary with authorized investigators (Database:databrary.org/volume/434).

EXPERIMENTAL MODEL AND SUBJECT DETAILS

Participants
We tested 32 children from 3.13 to 4.96 years of age (M = 4.03 years; 14 girls) and 22 adults (M = 21.90 years; 13 women). Data from 9 additional children and 4 adults were excluded because the technology malfunctioned (n = 9), children refused to wear all the technology (n = 3), or the participant was ambidextrous (n = 1). Participants were recruited from the New York City area. All participants had normal vision (or wore contact lenses); none had cognitive deficits or neurological problems. Participants received a robot toy, photo magnet, and tote bag for participation.

We determined children's hand dominance based on parents' report of the hand children used to brush their teeth, cut with scissors, and hold a spoon or fork, and laboratory observations of the hand children used to cut with scissors and draw a line (two trials with each task). Based on uniform responses across every parent report measure and observational measure, 29 children were right-handed, and 3 were left-handed; and 18 adults were right-handed and 4 were left-handed.

Due to technical issues (children moved before the robotic screen opened, EEG data were noisy, or recording devices malfunctioned), M = 3.72 trials per participant were excluded from the EEG and motion tracking analyses.

METHOD DETAILS

Procedure
Participants' task was to pound a peg with a wooden hammer (12.5-cm long handle, cylindrical hammerhead with a length of 6.5 cm and a face diameter of 2.5 cm). The peg (2.5-cm diameter) protruded 5 cm above the pegboard and was painted blue to contrast with the wooden pegboard (Figure 1A). Each 60-min session began by showing participants the head-mounted eye tracker, EEG cap, and motion tracking sleeve. (To motivate children to wear the recording devices, we told them it was a "robot costume," and presented them with the robot toy they would take home.) We fit participants with the recording devices and collected calibration data for the eye tracker. We put an oven mitt on participants' non-dominant hand to prevent them from using it to grasp the hammer (Database: databrary.org/volume/707).

For the hammering task, participants sat at a small table facing the experimenter and a robotic screen (Figure 1C and Database: databrary.org/volume/707). The screen (LEGO Mindstorm NXT) could open and shut to control when the hammer and pegboard were revealed and to facilitate synchronization among recording devices. The experimenter showed participants the hammer and peg and told them to "pound the peg with the hammer." The hammer rested on two blocks 16.5 cm apart so that participants could easily use either an overhand or underhand grip to grasp the handle.

Before each trial, the screen was closed, and participants placed their dominant hand on a red handprint on the table. Trials began when the screen opened to reveal the handle of the hammer pointing toward participants' dominant or non-dominant

hand. Participants completed 60 hammering trials presented in 4 blocks of 15 trials—5 habitual trials, where a habitual overhand grip was most efficient because the handle pointed toward participants' dominant hand, and 10 nonhabitual trials, where an underhand grip was most efficient because the handle pointed toward participants' non-dominant hand (Figure 1A), with presentation order pseudo-randomized. Between trial blocks, participants completed engaging filler tasks and children received stickers to maintain their motivation.

Recording Devices
Third-person cameras
Sessions were videotaped at 30 fps from overhead and side views so that all actions were visible. An additional magnified side view of the hammer clearly captured the initial grip. Camera views were synchronized and mixed into a single video online, which was then synced offline with the eye-tracker videos for ease of video coding and data processing. Third-person and eye-tracker videos were synchronized with a light flash at the beginning and end of each session and combined using Adobe Premier to produce a composite video for coding.

Motion tracker
A magnetic motion-tracking sensor (Ascension, 3D Guidance trakSTAR) with a long-distance transmitter (144 cm) was attached to participants' dominant hand to record their precise movement trajectories (500 Hz) and to synchronize the EEG data with the video data. We synced the motion tracker, EEG, and video using a custom-built box that sent a sync trigger to the EEG and motion-tracking recording and flashed an LED light (shown in the video) at the same time. The sensor was placed inside a "sleeve" that held all the trailing wires and positioned the sensor on participants' dominant wrist.

Head-mounted eye-tracker
As in previous work,[20,44] participants wore a Positive Science head-mounted eye tracker (www.positivescience.com) so that we could record where they looked (Figure 1C). The equipment consists of child- or adult-sized eyeglass frames, a transmitter, and a battery pack (total weight 375 g). We attached the headgear to the adjustable EEG cap for stability and connected it via wire leads to a computer on the far side of the room. Participants also wore a wide rubber belt with Velcro patches to secure the leads, transmitter, and battery pack to their back (Figure 1C and Database: databrary.org/volume/707). The eye tracker includes two small cameras mounted on the eyeglass frames—one to record the right eye (illuminated with an infrared emitting diode), and one to record the scene ($54.4° \times 42.2°$ field of view). We used PSLiveCapture to monitor both videos online. To calibrate the tracker, seated participants fixated on a display board placed $45°$ from their eyes to capture the entire table as the scene. Yarbus software synced the videos from the two cameras offline. We then calibrated the data offline by manually indicating the target locations. The software superimposes a $4°$ radius circular cursor on the composite video to denote the point of gaze on each video frame with a spatial accuracy of $\sim 2°$.

EEG. Participants wore a child- or adult-sized, wireless, 32-channel EEG cap (Neuroelectrics, ENOBIO 32, 500 Hz). Data were recorded from 32 scalp electrodes at locations of the extended 10-20 system and from two electrodes on the right mastoid. The single-ended voltage was recorded between each electrode site and CMS/DRL electrodes. In five children, we recorded only 4 electrodes (FC1, FC2, FC3, FC4) due to technical malfunctions.

Video Coding
Coders used Datavyu (www.datavyu.org), a computerized video coding tool, to identify the presence or absence of specific behaviors and their duration (see coding manual in Database: databrary.org/volume/434/slot/45990/).

Initial and end grips were participants' first grasp of the hammer (Figure 1A) and how they held the hammer when they pounded down the peg. Each grip was scored as overhand (palm down) or underhand (palm up) and as radial (thumb facing hammerhead) or ulnar (thumb facing away from hammerhead). *Grip changes* from the initial to end grip were changes after grasping the hammer.

Planning time was the duration from the first video frame when the screen lifted to the first video frame when participants lifted their hand from the table (i.e., their reaction time). *Movement time* was the duration between the first video frame when participants lifted their hand until the first frame when the hammer touched the peg. *Reach-to-grasp time* was the duration between the first video frame when participants lifted their hand until the first frame when their hand touched the hammer.

Last-moment changes in grip decision referred to trials when participants changed their decision about their initial grip part way through their initial reach. Coders considered a trial to have a last-moment grip decision if there was at least one frame in which they moved their hand backward before touching the hammer during their initial reach (see example in Database: databrary.org/volume/434/slot/51706/).

Implementation errors were how many times participants missed the peg on each trial (hammer did not touch the peg).

Gaze location was based on the location of the gaze cursor in the eye-tracking video. Coders scored every fixation to 3 regions of interest (ROIs): the hammer, peg board, and dominant hand. Gaze location was coded from screen opening to movement onset.

To ensure inter-observer reliability, a primary coder scored 100% of each participant's data, and a second coder scored 25%. Coders agreed on 99% of initial and end grips (ks = 0.96 and 0.98, respectively, $ps < 0.01$), 97.53% of implementation errors (k = 0.93, $p < 0.01$), 97.66% of last-moment grip decisions (k = 0.76, $p < 0.01$). Correlation coefficients between the two coders for coding reaction, movement, and looking times were $rs > 0.93$, $ps < 0.01$.

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QUANTIFICATION AND STATISTICAL ANALYSIS

Motion tracking: Data Processing and Analysis

Kinematic data were analyzed using the MATLAB Signal Processing toolbox. We compared the reaching trajectories for habitual and nonhabitual trials from reach onset until we identified the first moment when the trajectories differed. Preprocessing included a notch filter at 50 Hz and a band-pass 4th order Butterworth filter (5–500 Hz).

We determined differentiation in reaching trajectories in an iterative procedure. We started by taking the trajectory of each trial (that is, the x,y,z location of the sensor on participants' dominant hand) from 0 to 20 ms after movement onset. Then, for each pair of trials, we calculated the 3D Euclidean distance between the two trajectories:

$$(a) \quad d_{i,j} = \sqrt{\sum_{t=1}^{n}(x_i - x_j)^2 + \sum_{t=1}^{n}(y_i - y_j)^2 + \sum_{t=1}^{n}(z_i - z_j)^2}$$

where i and j signify two different trials, n is the number of time points, x is the location of the sensor in the x axis, y is the location of the sensor in the y axis and z is the location of the sensor in the z axis. If the distances between trials within the same condition was significantly smaller than the distances between trials across different conditions, we considered 20 ms as the moment of trajectory differentiation. If not, we increased the trajectory to the next time point (2-ms increments), and performed the same procedure (i.e., we increased the n in formula a) until we got a significant difference between distances within the same condition and distances across different conditions (measured by non-equal variance t test) or until n equals the length of the shortest trajectory. We could not perform this test for time points longer than the length of the shortest trajectory because we cannot apply formula a on trials with different lengths. Figure S2 shows a schematic illustration of the procedure.

Because there were unequal numbers of habitual and nonhabitual trials, we randomly selected trials from each condition according to the minimum number of trials across conditions and repeated the selection process 1000 times. We corrected for multiple comparisons by controlling the False Discovery Rate[45] with a threshold of q(FDR) < 0.05.

Eye tracking: Heatmaps and Distribution of Attention

We used a novel digitizing method for head-mounted eye tracking to record moment-to-moment changes in participants' gaze from screen opening to movement onset. Using custom-built MATLAB software, coders manually digitized the location of the hammer and the peg at each frame of the eye-tracking video. Gaze location was obtained from the eye tracker and was verified by human coders. We used the xy coordinates of the hammer and peg to rotate, shift, and scale the location of the gaze, hammer, and peg in each frame such that all frames were aligned with the hammer located at the center and the peg located above the hammer. This procedure allowed us to compare looking patterns around the task-relevant objects in the scene across frames and participants, although their location changed constantly with the head-mounted eye tracker (unlike desk-mounted eye trackers, where locations are fixed).

Based on the aligned data, we generated looking heatmaps for each participant and calculated the distribution of visual attention around the scene from screen opening to movement onset. Heatmaps were created by dividing the number of video frames each pixel was fixated (within a 75-pixel radius of participants' gaze location to account for detection resolution) across all trials and participants in the group by the total number of video frames. The distribution of attention was calculated at the trial level by counting the number of pixels that were fixated (or were within the 75-pixel radius) during the pre-movement interval of each trial.

EEG: Data Processing and Analysis

EEG data were analyzed offline using the EEGLAB tool for MATLAB.[46] Raw data were band-pass filtered offline between 1 and 40 Hz (Butterworth filter, 24 db), and re-referenced offline to the digital average of the two mastoids. Deflections from eye movements and blinks were corrected using independent component analysis. Epochs were extracted trial by trial for each time interval, with 0-1500 ms prior to the screen lifting as the baseline.

For removing ocular artifacts, we used independent component analysis (ICA) implemented in the EEGLAB toolbox. Ocular ICA components (range across participants = 1–2 components) were identified by visual inspection and deleted from the global signal. Noisy trial epochs (exceeding ± 250 µV range) at FCz, Cz, CPz, FC1, FC3, FC2, FC4, C1, C3, C2, C4, CP1, CP2, CP4 channels were identified in the raw data and rejected from analyses. Data from other electrodes were not used due to low signal-to-noise ratio.

We tested differences between habitual and nonhabitual trials in readiness potential—the average event-related potential before reach onset that corresponds to action planning, recorded from frontal and central regions.[47] For each participant, we calculated the signal in the time window 500 ms prior to reach onset at components with activity over the contralateral primary motor cortex to the executing effector (components were identified by visual inspection). We then compared the signal in the habitual and nonhabitual trials from reach onset backward until we identified the first moment when the signals significantly differed. To address the unequal number of habitual and nonhabitual trials, we performed similar significance procedures as in the motion-tracking analysis.