First “Where” and then “How”: Developmental Processes in Exploring Solutions to Problems with Hidden Demands

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Abstract

The required actions to solve many everyday motor problems are not immediately apparent. How do children discover these hidden demands? Exploration was assessed in 24- to 56-month-olds (*n* = 47; 26 girls) by tracking how children touched a tablet screen to open “virtual cabinets” with different locks. Children were strategic explorers. Hypothesis-driven exploration increased with age by first focusing on the appropriate area (“hypothesis” about where to act) and then on the appropriate action (“hypothesis” about how to act). Even when children did not hypothesize about where and how to solve the problem, they showed more directed than random exploration, and directed exploration increased with age. However, children did not generalize exploration of hidden demands from one problem to another.

Keywords: motor development; problem solving; exploration; task demands; discovery; tablets

Introduction

Young Children Are Avid Explorers

Motor exploration is essential for the development of functional behavior. Young children have limited knowledge about how things work because they have limited experience solving everyday problems like how to slide open a cabinet latch, twist open a container lid, grasp the handle of a tool, or fit an object into an aperture. Without observing more knowledgeable others or being told what to do, children must perform a variety of exploratory movements to discover *where* and *how* they should act to solve motor problems. For example, where is the closure on the cabinet, and how does the latch operate?

Developmental research is replete with illustrations of how infants and young children use visual and manual exploration to acquire knowledge and reduce uncertainty about their environment (Adolph & Robinson, 2015). For example, infants and young children explore objects by squeezing, fingering, rotating, and transferring objects from hand to hand, and by manipulating objects in relation to surfaces or other objects (Belsky, Goode, & Most, 1980; Bourgeois, Khawar, Neal, & Lockman, 2005; McCarty, Clifton, & Collard, 2001; Palmer, 1989; Soska & Adolph, 2014). Although children often perform such exploratory actions with no explicit goal imposed (Gottlieb, Oudeyer, Lopes, & Baranes, 2013; Oudeyer, Baranes, & Kaplan, 2013), nongoal-directed exploration can sometimes reveal what actions are possible. And in doing so, exploration informs a rich internal representation of the world that can be later used to guide goal-directed action (Kosoy et al., 2020; Schulz, 2012). Indeed, nongoal-directed exploration at an earlier age can be used to solve motor problems such as tool use at a later age (Kahrs, Jung, & Lockman, 2012; Lockman, 2000; Lockman & Kahrs, 2017). Moreover, nongoal-directed exploration plays an important role in facilitating higher-level cognition about how things work in the world (Gerson & Woodward, 2013; Sommerville, Woodward, & Needham, 2005; Woodward, Sommerville, & Guajardo, 2001).

Hidden Area and Action Demands

For some tasks—even novel motor problems—visual information for where and how to act is readily available. For example, children can immediately see that they must turn their hand to grasp a tilted rod (Lockman, Ashmead, & Bushnell, 1984), scrunch their hand to poke a finger into an aperture (Ishak, Franchak, &

Adolph, 2014), or rotate a block to fit it into a shape sorter (Jung, Kahrs, & Lockman, 2015; Jung, Kahrs, & Lockman, 2018; Ossmy, Han, Cheng, Kaplan, & Adolph, 2020). However, many everyday motor problems require *non-obvious actions* in a *particular area* of the object (Norman, 1999, 2013). The “where” and “how” for the solution must be discovered by active visual-manual exploration (Albrechtsen, Andersen, Bodker, & Pejtersen, 2001; Gaver, 1991; Hartson, 2003). The initial solution is “hidden.” Touch-latch cabinets are a prime example. The cabinet door stays shut via a ratchet and spring mechanism on the back of the door and opens with a firm press on the location housing the mechanism. For the uninitiated (even adults), the critical area and action are not obvious because the face of the cabinet has no visible latch and the pressing action is not specified. Likewise, many containers, shower fixtures, and doors present similar challenges (Norman, 2013).

How do children discover hidden areas and actions? With nongoal-directed exploration, problem demands can be so buried that children fail to recognize what they did if they eventually solve the problem—indeed, they are likely to fail to recognize the “problem.” With goal-directed exploration, children intend to bridge the gap between what they already know and what they need to know to achieve a goal. Thus, children *purposefully* attempt to open the cabinet door or container by exploring and testing multiple solutions until they discover the location of the critical area and how to act on it.

Developmental Changes in Exploring Hidden Demands

Out of all possible areas and actions, how do children hone in on the right ones? In principle, hidden demands will be discovered for certain if children try every possible action in every possible area. However, exploring every combination of areas and actions—either systematically or randomly—is grossly inefficient. The number of possibilities is simply too large.

Instead, exploration must be guided toward the target area and action to reduce the search space. But what guides children’s exploration of problems with hidden demands? Many everyday problems—opening containers with twist-off or pull-off lids or pouches with zipper closures—seem simple, but children can solve them only if they actively explore the relevant area and required actions. In these tasks, children show an age-related progression in exploratory behaviors (Rachwani, Kaplan, Tamis-LeMonda, & Adolph, 2021; Rachwani, Tamis-LeMonda, Lockman, Karasik, & Adolph, 2020). Toddlers' exploration is guided by the readily available visual information and affordances (e.g., rotating or banging the container, squishing and pulling the sides of the pouch). Such non-directed exploration may provide new haptic information about the object that can guide children to the *target area* of the search space (the edges of the container lid or the wiggly zipper tab). At older ages, children exhibit goal-directed exploration by immediately honing in on the target area, which further narrows the search space by drawing children toward the *target actions* (twisting the lid back and forth or pulling the zipper tab at various angles), which in turn generates haptic information, until children finally implement the successful solution (twisting the lid repeatedly to the left or pulling the zipper tab at the appropriate angle).

Current Study

To deepen our understanding of how children learn to solve motor problems with hidden demands, we assessed how children solve such motor problems with no haptic information to guide their exploration. We hypothesized that children improve with age by attempting to discover *where* they should act *before* attempting to discover *how* they should act. That is, children learn to look for the hidden area first and then look for the hidden action demands. This is because knowing the area narrows down the possible actions, but without the target area to guide them, the number of possible actions is extremely large. For example, identifying the target area as the cabinet lock or container lid eliminates those actions not afforded by manipulating the lock or lid.

To test this hypothesis, we encouraged children to open "virtual cabinets" as a model system to characterize developmental and real-time changes in exploration. As in Pelz & Kidd (2020), we documented age-related changes in how children touched a tablet screen. This fine-grained quantification of children's exploration patterns has better temporal and spatial accuracy compared to experiments in a real, physical environment that rely on general descriptions of the action and area (e.g., pressing the lid, banging the container). Critically, children's only haptic feedback with the tablet came from touching the flat screen, regardless of their selected exploratory area or action. Nothing in the physical properties of the screen guided children toward the target area or action. The tablet had no constraints on what areas could be explored and children experienced no physical costs or tangible rewards for their actions.

With our virtual cabinets (Figure 1A), children had to open a virtual "lock" to liberate a cartoon animal visible behind a transparent window on the face of the cabinet. There were two possible locks (slider to the left or slider to the right; Figure 1B). Each child started with one of the locks for 6 trials, and then the lock switched and the child attempted to open the new lock for another 6 trials. Thus, the exact demands for area and action in this motor problem were hidden. The *target area* and *target action* had very strict tolerance limits (Figure 1D). Touches had to start and end at specific locations on the lock (see green lines in Figure 1D); if not, the door remained closed. Moreover, the required movement was arbitrary (sliding to the left or right), and the visual information to specify it was ambiguous (the yellow lock looks like a button that can be pressed; Figure 1B). To fill a critical gap in the literature on motor exploration that focused on infants and grade-school children, we designed the game for preschoolers and tested 24- to 56-month-olds (Figure 1C).

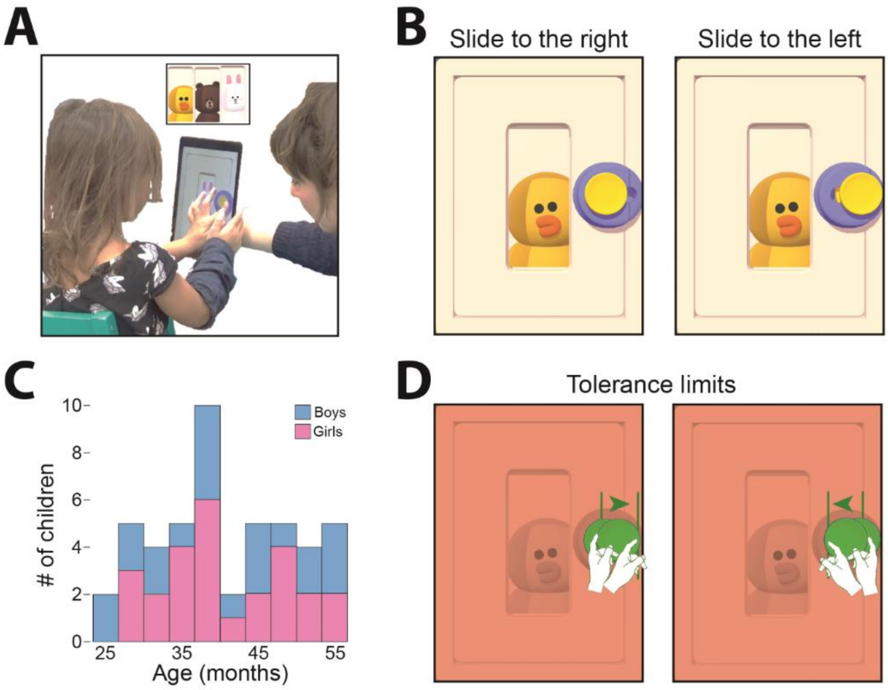

Figure 1. **The "virtual cabinets" tablet game. (A)** Children were encouraged to open a virtual "lock" to get an animal out of a cabinet. Inset shows the three cartoon animals used in the game. Each animal appeared 4 times in random order. **(B)** Two lock types—sliders that opened to the right or the left. **(C)** Number of children tested by age and sex. **(D)** Tolerance limits for opening the locks. Green arrows and cartoon hands show the required movement and direction. Green circles indicate the permissible touch area to move the lock. Red areas indicate locations outside the permissible touch area. Green bars indicate where children needed to start and end their touches to open the lock. If the touch began or ended beyond the bars, the lock did not open.

We first tested whether children could succeed in opening the virtual cabinets or failed to discover the hidden demands due to lack of haptic information. We expected that older children would open the cabinets more frequently, faster, and with fewer touches than younger children and that success would increase faster over trials with child age.

Then, we asked how children attempted to open the virtual cabinets. We used a cognitive approach to motor exploration (Alison Gopnik, 2012; Ruggeri, Xu, & Lombrozo, 2019; L. Schulz, 2012), by assessing children's "hypotheses" regarding where to explore (area hypothesis) and how (action hypothesis). If, as we expected, children show an age-related increase in successful openings and within-session learning across trials, then exploration cannot be random and must be guided by some factor. Therefore, we predicted more hypothesis-based exploration with age and across trials. Critical to our experimental hypothesis, we predicted that *children would generate hypotheses about the critical area before generating hypotheses about the required action*.

Finally, we assessed whether children generalize their area and action exploration from one problem to another. Presumably, experience in exploring hidden area and action demands of one problem provides knowledge that can narrow down the search space for other hidden area and action demands. To test generalization, we compared how exploration changed from one trial to the next *within* the same problem (i.e., same lock) to changes *across* problems (i.e., after the lock switch). That is, if changes in area/action hypotheses between trial 6 (the last trial before the lock switch) and trial 7 (the first trial after the lock switch) are similar to changes in area/action hypotheses between the rest of the trials, we could conclude that children generalize area/action from their previous exploration. But if the number of area or action hypotheses drops from trial 6 to trial 7, and does so significantly more than the change in hypotheses between other trials, we would conclude that children do not generalize their knowledge from previous exploration.

Method

Data and Code Sharing

Videos of participants' sessions are publicly available in the Databrary web-based library (databrary.org/volume/1415). With participants' permission, third-person videos of their behaviors and demographic data are also shared in Databrary with authorized researchers.

Participants

We tested 47 children from 2.05 to 4.83 years of age (M = 3.47 years; 26 girls; Figure 1B). Children were recruited from advertisements, referrals, and a pool of families who expressed interest in participating in research when their children were born. Children received a $40 gift card, robot toy, photo magnet, and tote bag as souvenirs of participation. All participants were typically developing with normal vision. One additional participant was excluded because he was not interested in the game.

“Virtual Cabinets”

We designed a problem-solving game on a digital tablet (iPad Air, iOS12.5.1, Apple Inc.) in which children were encouraged to open the door of a virtual cabinet to release a cartoon animal (duck, bear, or bunny) visible behind a glass window on the door of the cabinet (Figure 1C and databrary.org/volume/1415). The cabinet opened with two types of locks—a slider that opened to the left (Figure 1C, left panel) or to the right (Figure 1C, right panel). We set strict tolerance limits for opening the cabinets that required perfect slides—children had to touch the tablet at the center of the lock, make a short slide in the correct direction and then lift their finger after they brought the virtual knob to the edge of the lock (Figure 1D)

Each child received 2 blocks of trials: (1) six trials with the left-sliding lock; and (2) six trials with the right-sliding lock, with block order counterbalanced across participants (24 in order 1). If the child did not open the lock within 20 seconds, the trial ended and the game continued to the next trial. Each animal appeared in 4 trials in random order.

The game was programmed in C# programming language within the Unity Engine developing environment (https://unity.com, version: 2018.3.3f1) and was exported as an application to the iPad through Apple XCode. All 3D assets in the game were modeled using Maya (https://www.autodesk.com/products/maya, 2018). The cartoon animals (duck, bear, or bunny) were based on Line Friends (https://www.linefriends.com) characters.

Procedure

The virtual cabinet game was administered at the end of a larger study on children's manual actions. The experimenter gave children the tablet and asked them: "Can you get the bunny/bear/duck out?" She repeated the sentence for each trial, sometimes several times per trial. We recorded children from a third-person camera view (30 fps) and from the tablet's frontal camera (24 fps). The two camera views allowed validation of children's attention and their level of engagement with the game (see videos of participants at databrary.org/volume/1415).

Data Processing

Touch Types. The iPad tracked children's touches (finger position) at each moment, their success at opening the lock, and the duration of each trial. We focused on how and where children touched the screen during each trial. For each touch, we calculated (1) *touch distance*—number of pixels in the touch trajectory; (2) *touch repeated area*—ratio between the number of touched pixels overall and unique touched pixels; (3) *touch on lock*—proportion of touched pixels on the lock; and (4) *touch on window*—proportion of touched pixels that were part of the cabinet window.

Based on these measures, we labeled the *area* and *action* of each touch (Table S1). We labeled touch area as either "lock" (*touch-on-lock* greater than 90% of the total fingertip area), "window" (*touch-on-window* greater than 90% of the total fingertip area), or "other" (both *touch-on-lock* and *touch-on-window* less than or equal to 90%). Based on the capabilities of the tablet, we labeled touch actions as either "press" (*touch distance* equals 1 fingertip area), "repetitive slide" (*touch distance* longer than 1 fingertip area and *touch repeated area* larger than the median across the entire dataset), "short slide" (*touch distance* longer than 1 fingertip area and less than or equal to the size of the lock, and *touch repeated area* smaller the median across the entire dataset), and "long slide" (*touch distance* larger than the size of the lock and *touch repeated area* smaller than the median ratio across the entire dataset).

Area and Action Hypotheses. For each trial, we determined whether children generated hypotheses about the target area and target action by examining the distribution of touch types within the trial. For area hypotheses, we assessed whether the child touched one of the areas (lock, window, or other) on more than 66.6% of the touches in the trial (such that the other areas were necessarily at chance levels). If there was no such area, we determined that the child had "no area hypothesis" for the trial because there was no single dominant touch area. Given a dominant area, we considered the child had a "true hypothesis" if that area was the lock (the target area) or a "false hypothesis" if that area was either the window or other (not-target areas). Figure 5 (left panel) shows an example for each area hypothesis.

For action hypotheses, we assessed whether the child used one of the actions (press, repetitive slide, short slide, or long slide) on more than 75% of the touches in the trial (such that the other touch types were necessarily at chance levels). If not, there was no dominant action and we considered the trial to have "no action hypothesis." Given a dominant action, we considered the trial to have a "true action hypothesis" if the dominant action was the short slide (the target action) and a "false action hypothesis" otherwise.

Random and Directed Exploration. Inspired by cognitive research, we examined whether children used random or directed exploration (Meder, Wu, Schulz, & Ruggeri, 2021). Random exploration is characterized by high levels of randomness in the selection of where and how to explore. This means there is no guiding rule to what type of touch children choose at each moment. Directed exploration actively seeks out uncertainty. This means that children select where and how to explore based on their past behavior and prioritize actions and areas that were previously selected less often.

We assessed children's random exploration for each trial by running a randomness test (MATLAB's runstest function) on the sequence of actions within the trial. We used the p-value from this test as *REI*—random exploration index that indicates the level of randomness in the trial. Thus, the value range for the *REI* is 0 to 1.

Directed exploration was assessed for each trial by calculating the DEI—the probability to select the "least-selected" action in each touch within the trial, according to the following:

$$DEI = \frac{\sum_{i=2}^{n} f(t_i, i)}{n-1} \qquad (1)$$

Where

$$f(x,i) = \begin{cases} 1, & C(x,i) = \min\big(C(1,i) \ldots C(4,i)\big) \\ 0, & otherwise \end{cases} \qquad (2)$$

$$C(x,i) = \sum_{k=1}^{i-1} [t_k = x] \qquad (3)$$

where *n* is the number of touches in the trial, and t_i is the type of touch *i*. Possible values for t_i are 1 to 4, indicating the different actions. We used the *DEI* as an index for the level of directed exploration in the trial. Similar to the *REI*, the value range for the *DEI* is 0 to 1.

Results

Most children (87.23%) completed all 12 trials, *M* = 11.53 (*SD* = 1.70). Preliminary analyses showed no effect of gender, so it was collapsed in subsequent analyses.

Success Rate and Trial Duration

Children successfully opened the lock on *M* = 57.46% (*SD* = 40.37%) of trials. Figure 2A shows each child's success on each trial. As we expected, success rates (top panel) increased with age, *r*(45) = .77; *p* < .00. Fitting a sigmoid function to the data (black line in Figure 2A top panel; slope = .09) shows that children become more successful after 38.52 months. Moreover, children succeeded faster with age (Figure 2B, top panel, *r*(45)=-0.55, *p*<.00).

As we also anticipated, children became more successful (Figure 2A, right panel) and faster (Figure 2B, right panel) across trials. However, success rate dropped after we flipped the direction of the lock (see yellow box in Figure 2A showing a difference in performance between trials 6 and 7). However, when children did succeed, the lock change did not affect how quickly they succeeded (yellow box in Figure 2B).

Overall, the number of touches per trial (*M* = 9.86, *SD* = 8.28) did not decrease with age, *r*(45) > -.23, *p* > .11. However, when we split the data into successful and unsuccessful trials, we found a significant developmental change. Fewer touches was associated with increasing age for successful trials, *r*(45) = -.38, *p* < .01 (Figure 3A), and more touches was associated with increasing age for unsuccessful trials, $r(45) = .29$, $p < .05$ (Figure 3B). These findings suggest that children changed their exploration with age and experience in the task.

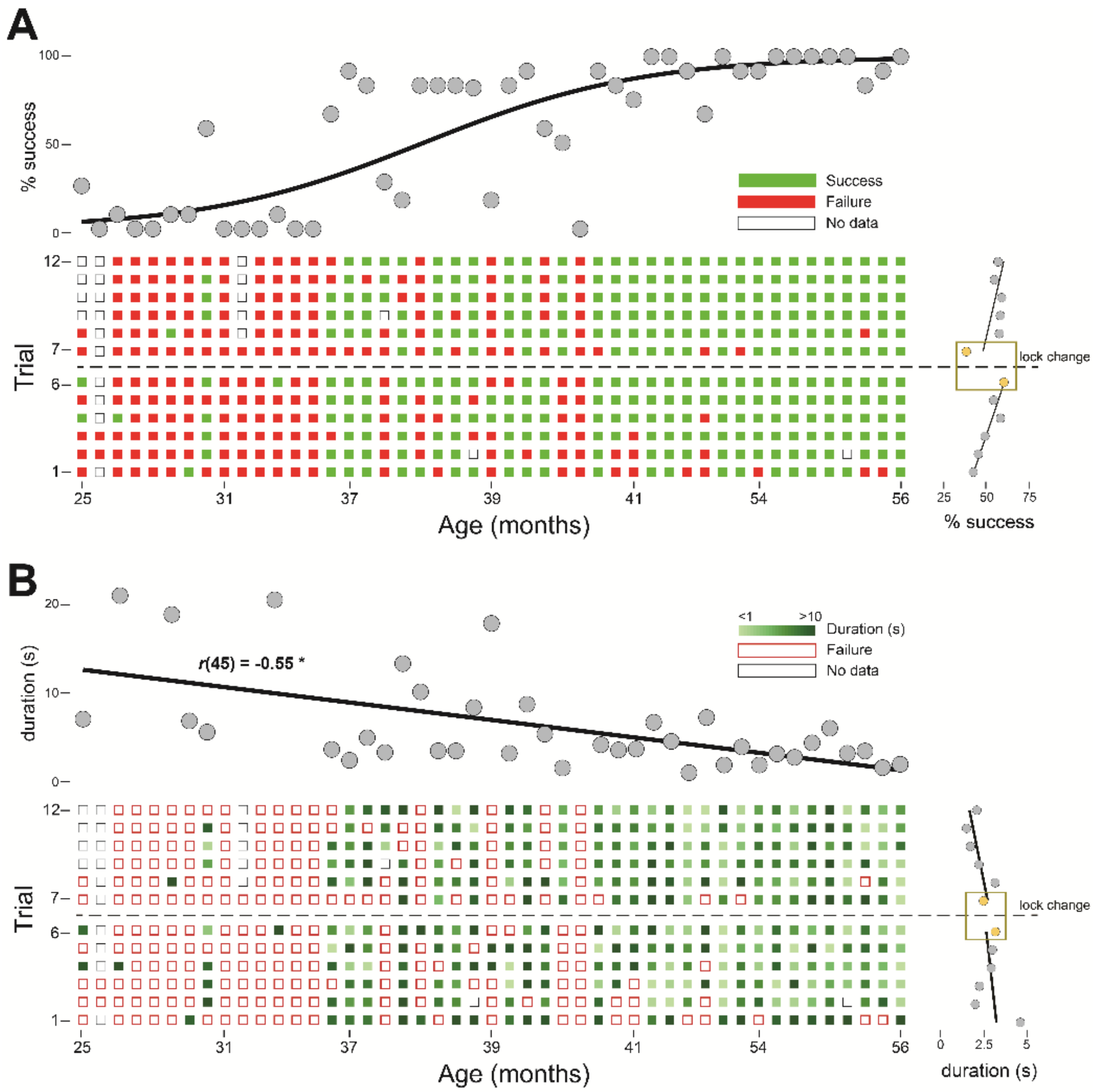

Figure 2. Task performance. **(A)** Success rates increased with age and experience (within session). Each square indicates one trial of one child and its color indicates success (green), failure (red) or missing data (empty). Scatter plot on the top shows success rate by age. Each grey dot is one participant. Sigmoid function (black line) fits the data and reveals that children become more successful in the task after 38.52 months. Scatter plot on the right shows success rate by trials. Yellow box indicates drop in success rate between the sixth and the seventh trial (switching the lock of the cabinet). **(B)** Trial duration decreased with age and experience. Because trials ended after 20 seconds in case of a failure, the analysis focused only on successful trials. Similar to A, each square indicates one trial of one child and its color indicates the duration for successful trials (going from light green for short trials to dark green for long trials), failed trials (empty square with red border), or missing data (empty with black border). Scatter plot on top summarizes data across trials and shows significant decrease with age. Scatter plot on the right summarizes data across children and shows decrease from one trial to the other. Yellow box indicates change in duration after lock switch. Unlike the drop in success rates, change in lock did not affect the time it took children to open the cabinet.

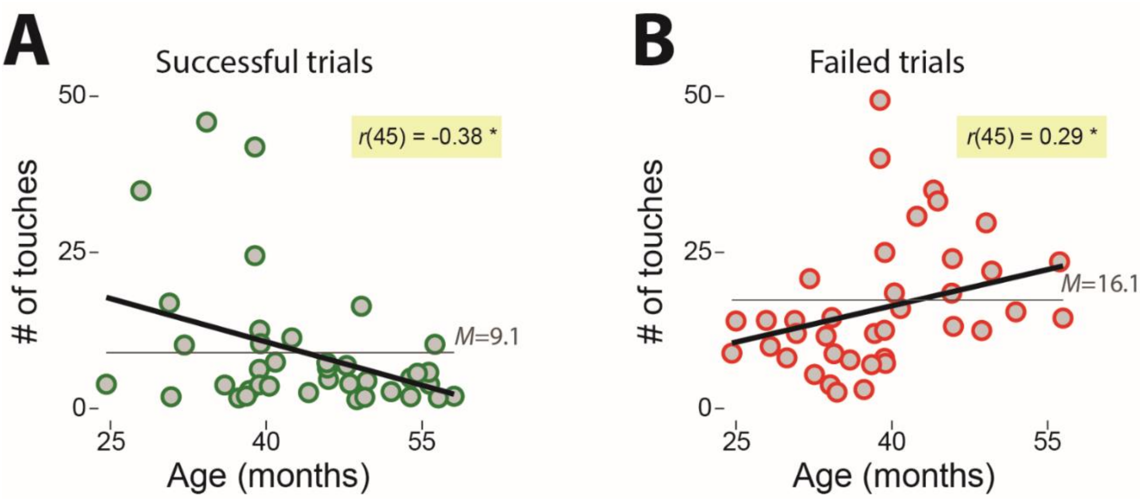

Figure 3. Number of touches by age. (A) Number of touches decreased with age when children succeeded and **(B)** increased with age if they failed. Asterisks and yellow squares indicate significance correlation.

Exploration of Area and Action

The touch data generated detailed streams of how children explored the problem. We determined the area and action of each touch based on 4 measures reflecting how children interacted with the screen—touch distance, touch repeated area, touch on lock, and touch on window (Table S1). Figure S1 shows the distribution of each measure and how it changes with age and across trials. Then, we labeled the action of each touch as either press, repetitive slide, short slide, and long slide, and the area of each touch as either lock, window, or other. Figure S2 shows how each touch area and touch action changed with age (panels A and C) and experience (panels B and D).

The heat maps in Figure 4 show touch data for one trial for a child who exhibited every type of touch in every area; the large heat map in the left panel shows touches accumulated over the trial; the small heat maps in the right panel correspond to each touch type and area. As shown by the bar graphs corresponding to each touch type and area in Figure 4, children did not display a dominant touch action, but they did display a dominant touch area—they focused more on the lock compared to the other two areas. A 4 (action) × 3 (area) repeated-measures ANOVA on the frequency of touches showed only a main effect for area, $F(2, 46) = 72.18$, $p < .00$, and an interaction between area and action, $F(6, 46) = 9.40$, $p < .00$. Sidak-corrected post hoc comparison tests showed that the lock was the most explored area, $p < .05$.

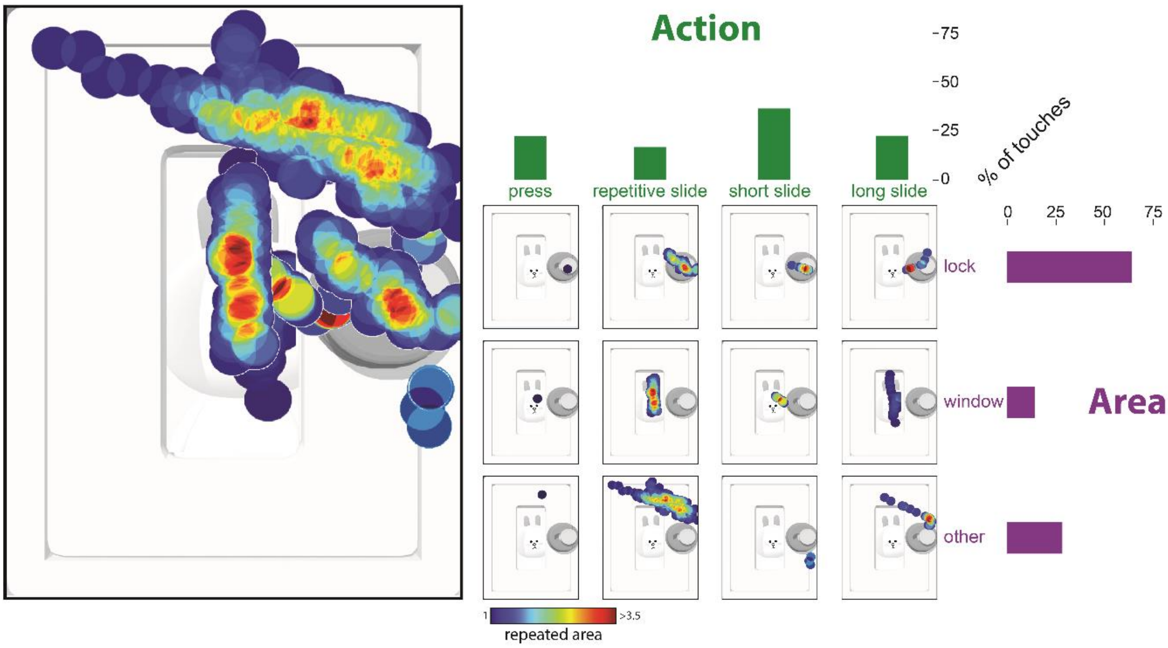

Figure 4. Touch types. We identified the area and action of each touch. There were 3 areas (lock, window, other) and 4 actions (press, repetitive slide, short slide, and long slide). Large image on the left shows an exemplar trial and heat maps represent where and how children touched the screen. The small images show the different touch types in the specific trial, ordered by area (rows) and action (columns). Bars on the right show the percent of touches per area and bars on top show the percent of touches per action. (see Methods and Table S1 for how we determined the area and action labels).

Area and Action Hypotheses

For each trial, we determined whether children generated hypotheses about the target area and action. Figure 5 shows examples of trials with no-hypothesis, false hypotheses, and true hypotheses about area and action. For no-hypothesis trials, the child shifted frequently from one area/action to another. For false-hypothesis trials, the child focused on one area/action that was not the target one. For true-hypothesis trials, the child focused on the target area/action.

As we predicted, children generated more hypotheses about area than action. The true area hypothesis was more frequent (M = 71.19% SD = 29.49 of the trials) than the true action hypothesis (M = 18.87% SD = 18.64). Accordingly, the no-area hypothesis was less frequent (M = 15.06% SD = 16.31) than the no-action hypothesis (M = 62.06% SD = 26.34). A 2 (targets: area and action) × 3 (hypotheses: no, true, and false) ANOVA on the percent of trials confirmed an interaction between target and hypothesis, $F(2, 46) = 90.21$, $p < .00$. Post hoc comparison tests showed that children generated true hypotheses about the target area and no hypothesis about the target action, $ps < .05$.

With age, children shifted from testing no hypothesis to testing true hypotheses about both the area (Figure 6, left panel) and action (Figure 6, right panel). Children also showed a similar shift from a no-area hypothesis to a true-area hypothesis with experience in the task (left panel, Figure 7; only children with all 12 trials were included). Experience, however, did not affect children's action hypotheses (right panel Figure 7). Taken together, these findings suggest that children generated area hypotheses before they generated action hypotheses, and area hypotheses were generated within the session (Figures S3 and S4 summarize children's area and action hypotheses respectively).

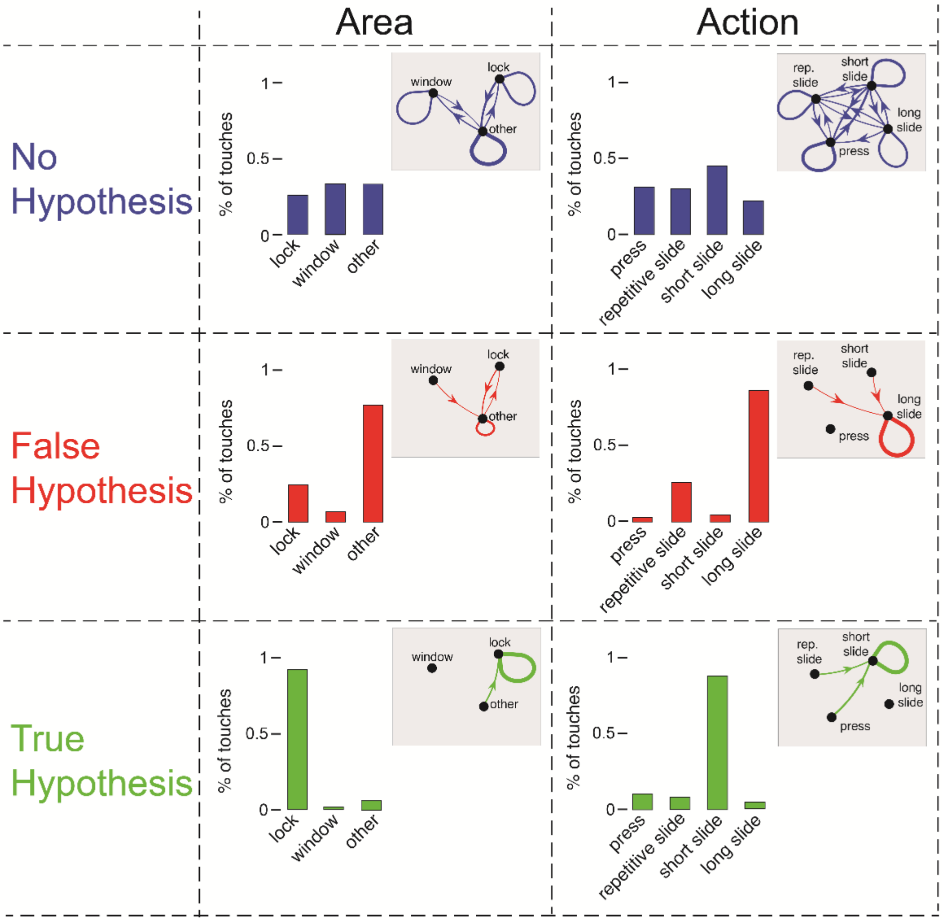

Figure 5. Area and action hypotheses. Example of six trials, representing no, false, and true hypotheses about area (left column) and no, false, and true hypotheses about action (right column). Hypotheses were determined based on the distribution and order of touch types within the trial (see Methods). Lines in the arrow diagram (grey boxes) represent the proportion of transitions from one area/action to another. Thicker lines represent higher proportions.

Inspired by cognitive research (Meder et al., 2021), we performed an exploratory analysis to test whether children used random or directed exploration on trials with no area or action hypotheses. (In trials with true or false hypotheses, children selected the area or action based on what they believed to be the area/action with the highest probability to result in success. So our focus in this analysis was on no-hypothesis trials.) Moreover, because no-area-hypothesis trials were infrequent (see Figure 6), there were not sufficient data to analyze random and directed exploration of area, so we limited the analysis to no-action-hypothesis trials. Figure 8 shows that on average, children used more directed exploration (measured by DEI) than random exploration (measured by REI). Moreover, we found a significant correlation between directed exploration and age, $r(45) = .39$, $p < .00$; the negative correlation between random exploration and age was only a trend, $r(45) = -.27$, $p = .06$.

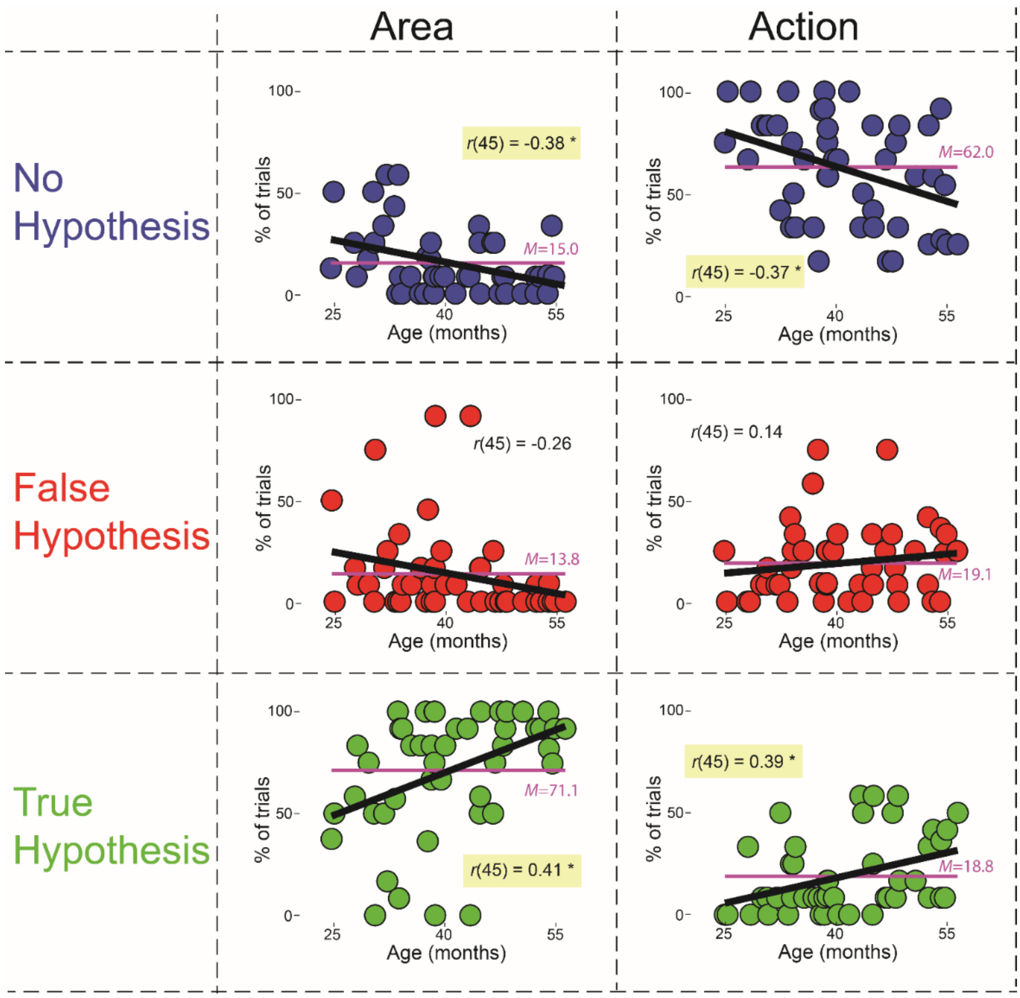

Figure 6. Change in hypotheses by age. For both area and action, children shifted from no-hypothesis trials to true-hypothesis trials. Yet, children had more true-area-hypothesis trials than true-action-hypothesis trials and in contrast, more no-action-hypothesis trials than no-area-hypothesis trials. Asterisks and yellow squares indicate significant correlations.

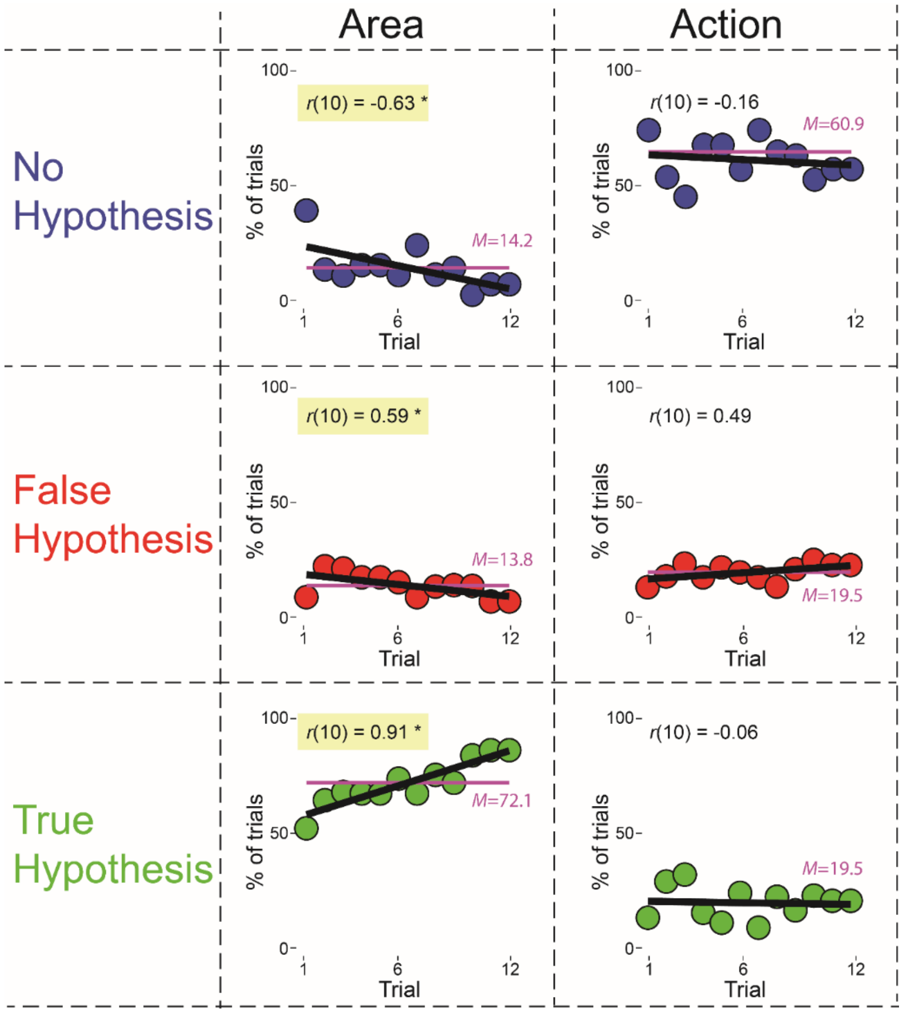

Figure 7. Change in hypotheses by trial number. No- and false-area-hypotheses decreased across trials. In contrast, true-area-hypotheses increased across trials (left column). We did not find any effect of trial number on action hypotheses (right column). Asterisks and yellow squares indicate significant correlations. Unlike Figure 6 that includes all children, this analysis included only children who completed all 12 trials.

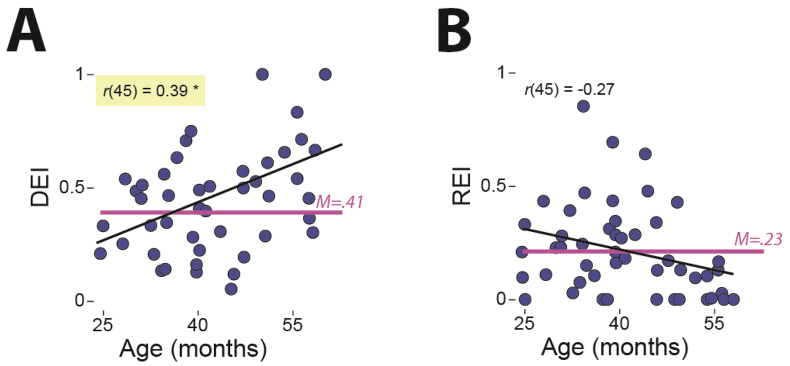

Figure 8. Directed and random exploration in no-action-hypothesis trials. (A) Children's directed exploration was measured by DEI (see Methods). We found that DEI increased with age when children did not have an action hypothesis. Asterisk and yellow square indicate significant correlation. **(B)** Children's random exploration was measured by REI (see Methods). REI decreased with age on no-action-hypothesis trials. Correlation was near-significant (p = .06).

Hypothesis Generalization

We examined how the number of no, false, and true hypotheses about area and action changed from one trial to another across the entire dataset. Specifically, we tested how children's hypotheses changed after we switched the lock. Over the entire dataset, children generated *M* = 6.52% more no-area hypotheses, *M* = 6.42% more false-area hypotheses, *M* = 15.21% more no-action hypotheses, and *M* = 2.17% more false-action hypothesis in in the first trial after switch compared to the last trial before switch (i.e., trial 6 compared to trial 6; Figure 9). Moreover, the number of true hypotheses decreased: Children had *M* = -13.04% fewer true-area hypotheses and *M* = -17.39% fewer true-action hypotheses after the lock switch (averaged across trial-transitions over the entire dataset). Figure 9 demonstrates that these changes in hypotheses across problems (after the lock switch) were significantly different from changes in hypotheses within each problem (same lock). When the lock was the same, children had fewer no-area and no-action hypotheses (*M* = -4.07% *SD* = 5.18, and *M* =- 2.26% *SD* = 9.70, respectively), fewer false-area and false-action hypotheses (*M* = -0.40% *SD* = 5.19, and *M* = -1.18% *SD* = 4.42, respectively), and more true-area and true-action hypotheses (*M* = 4.53% *SD* = 9.14, and *M* = 3.44% *SD* = 11.12, respectively).

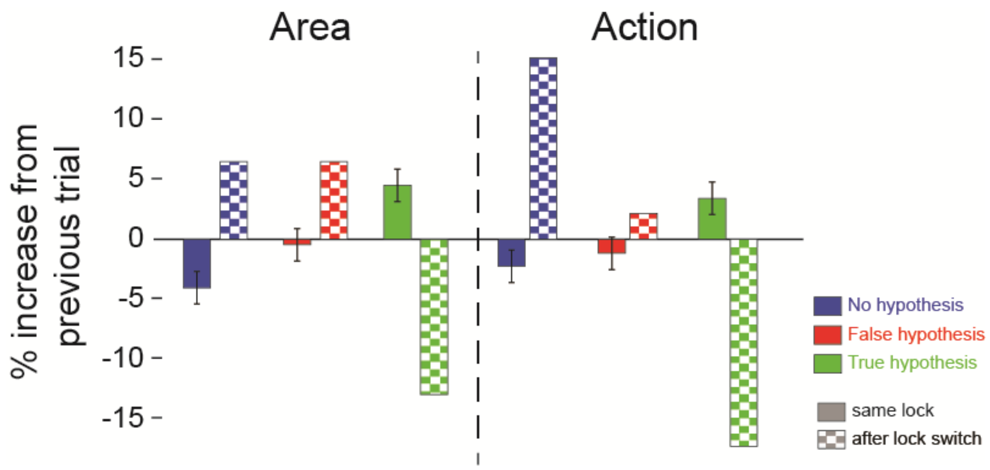

Figure 9. Hypothesis generalization. Bars show the mean change in hypotheses about area and action after the lock switch ("lock switch"—difference between trial 6 to trial 7 averaged across children) and when the lock remained the same ("same lock"—difference between consecutive trials, averaged across children). Standard errors for "same lock" bars indicate range across pairs of trials.

Discussion

We used opening of virtual cabinets as a model system to understand how young children solve motor problems where the visual and haptic information for the solution is hidden. Such everyday problems require strategic exploration because randomly trying out all possible solutions is highly inefficient and unlikely to result in success. Uncertainty-based exploration is more strategic because it is systematic. But hypothesis testing (first area, then action) is most strategic because it narrows the possible search space and thereby leads to a faster solution.

Children indeed were strategic explorers. Children improved with age by first focusing their exploration on the appropriate area (where to act) and then on the appropriate action (how to act). Moreover, when children did not "hypothesize" about where and how to solve the problem, they showed more directed, uncertainty-based exploration than random exploration, and directed exploration increased with age. However, children did not show significant generalization of hidden demands from one problem to another.

Area Before Action: Narrowing Down the Search Space in Motor Exploration

Prior research showed that adults use hypothesis-driven exploration when they solve motor problems (Newell & Simon, 1972; Schulz & Gershman, 2019). That is, adults generate and test hypotheses about specific solutions. If the hypothesis is correct, the problem is solved and if not, adults generate and test a new hypothesis, and so on. The heuristic is to generate hypotheses that narrow down the search space, reduce the amount of possible solutions, and thereby efficiently guide exploration to hone in on the right solution.

Children do the same (Gopnik, Meltzoff, & Kuhl, 1999; Legare, 2012; Meder et al., 2021; Ruggeri, Lombrozo, Griffiths, & Xu, 2016). As children explore, they make predictions to guide their information search (Denison & Xu, 2014, 2019; Gweon, Tenenbaum, & Schulz, 2010; Kushnir & Gopnik, 2005). With development, their hypotheses narrow down the search space more and more, making their exploration more efficient. For example, in a traditional version of the 20-questions game (Ruggeri et al., 2016), younger children ask questions targeted toward a specific solution (e.g., "is it a dog?"), whereas older children ask questions about categories or features (e.g., "is it an animal?") . Information about categories and features narrows down the search space, guiding children to find the correct answer with fewer questions. Thus, older children carefully select their questions and in doing, they greatly improve their odds of finding the answer.

The current study revealed a motor version of this heuristic hypothesis-testing exploration in young children. Similar to a careful selection of questions that constrain possible answers in the 20-question game, careful selection of area constrains the possible actions to solve motor problems. Children hypothesized about where they should touch before generating a hypothesis about the particular touch action. Moreover, children generated more area hypotheses from one trial to another but did not show a similar trend in generating action hypotheses. This finding suggests that children quickly learn that they need to narrow down the search space, and only then do they focus on the correct action.

In addition to narrowing down the search space, children became more efficient explorers by applying more directed exploration and less random exploration with age. This finding suggests that young children explore broadly whereas older children give more weight to the cost of exploration (e.g., the time to complete the task, energy, etc.). In other words, young children are more interested in learning what actions are possible and where, and older children are more directed toward solving the problem. These findings align with recent developmental work in a spatial grid-search game that combined behavioral data and computational modeling (Meder et al., 2021). Children showed a decrease in random exploration from 4 to 9 years of age, but a high amount of directed exploration at every age. Our findings expand these developmental trends to an earlier age and to the motor domain.

From a computational perspective, our findings contribute to understanding of the computational principles underlying the development of human exploration. The traditional computational approach defines exploration patterns in terms of the exploration-exploitation tradeoff—choosing a costly, unfamiliar option with an unknown outcome versus choosing a familiar option with a known outcome. In the "Bandit" task (participants repeatedly choose among alternatives that are characterized by different reward distributions; E. Schulz & Gershman, 2019), adults and children solve the trade-off differently. Children are biased toward exploration whereas adults are biased towards exploitation (Gopnik, 2020; Lucas, Bridgers, Griffiths, & Gopnik, 2014; E. Schulz, Wu, Ruggeri, & Meder, 2019; Seiver, Gopnik, & Goodman, 2013). Here, we show that during motor exploration, children solve the exploration-exploitation trade-off in a hierarchical manner—they first explore the area and then exploit the discovered area by exploring possible actions therein.

Generalization of Exploration

Another important aspect of the exploration-exploitation tradeoff is generalization—whether explorers generalize their experience exploring solutions in a specific problem to novel problems. Previous research showed that children generalize their exploration by using cognitive inference to predict outcomes of actions in a new problem based on action outcomes of a previously explored problem (Meder et al., 2021; Ruggeri et al., 2016). The notion is that children use previous knowledge gained during exploration to inform future actions in other situations. In the current study, however, children hypothesized less about both area and action when the problem was new (trials after lock switch). Although the area of the new problem was identical to the area of the previously explored problem (same lock area, different direction), children did not use their experience in previous trials to hypothesize about where to explore and to reduce the new problem space. Thus, at least when it comes to motor exploration of young children, generalization does not provide guidance for exploring area and action.

Moreover, even after children succeeded, they did not use the knowledge they gained by repeating the successful action, but rather children persisted in exploring alternative solutions. Nevertheless, failure prompted more exploration with child age, suggesting that when older children explore, they account for knowledge they discovered in previous exploration. This finding aligns with previous work showing that older children explore more when presented with confounded evidence (L. E. Schulz & Bonawitz, 2007). Future research should directly test the effects of knowledge gained during exploration on subsequent exploration patterns and how these effects change over development.

Implication for Real-World Robot Exploration

Little research uses child behavior to guide work in artificial intelligence (AI) and robotics (but see Kosoy et al., 2021; Kosoy et al., 2020; Ossmy et al., 2018). Many computational models for motor problem solving are based on presupposed concepts and are not grounded in real-time behavioral data, which impedes real-world applicability. Our findings are relevant to the embodied AI and robotics communities interested in building embodied agents that learn to solve real-world problems with hidden demands. Most algorithms of artificial embodied agents are based on reinforcement learning (Arulkumaran, Deisenroth, Brundage, & Bharath, 2017; Mousavi, Schukat, & Howley, 2016; Sutton & Barto, 2018), in which agents learn by receiving positive rewards for doing target actions and negative rewards for doing non-target actions. We propose that imbuing artificial embodied agents with children's "first where-then how" strategy will improve AI goal-directed exploration skills and lead to improved real-world problem solving. Thus, future embodied AI research should integrate experimental and computational approaches to children's motor exploration (e.g. Gershman, 2018; Kosoy et al., 2020). AI agents need not replicate children's motor skills to reveal new insights into the development of motor exploration.

Finally, humans serve as a useful baseline for evaluating performance of artificial embodied agents (Dubey, Agrawal, Pathak, Griffiths, & Efros, 2018; Mnih et al., 2015). We propose our virtual cabinet task as a computational challenge for exploration in the service of a goal. The simplicity of the problem (e.g., no haptic information, limited visual scene), direct quantification of the human actions (using the tablet), and the relevance to real life (opening cabinets is a common problem with hidden demands) is ideal for comparing goal-directed exploration between children and machines.

Conclusions

We investigated developmental changes in goal-directed exploration when children solve motor problems with hidden demands. Using a novel virtual game, we showed that children's motor exploration is strategic. Children first hypothesize about the area they should explore and then, after reducing the search space of possible actions, they hypothesize about which action they should use. Our findings provide a new perspective for cognitive-based research on human exploration and problem solving.

References

Adolph, K. E., & Robinson, S. R. (2015). Motor development. In L. Liben & U. Muller (Eds.), *Handbook of child psychology and developmental science* (7th ed., Vol. 2 Cognitive Processes, pp. 113-157). New York: Wiley.

Albrechtsen, H., Andersen, H. H. K., Bodker, S., & Pejtersen, A. M. (2001). *Affordances in activity theory and cognitive systems engineering*. Roskilde, Denmark: Riso National Laboratory.

Arulkumaran, K., Deisenroth, M. P., Brundage, M., & Bharath, A. A. (2017). Deep reinforcement learning: A brief survey. *IEEE Signal Processing Magazine, 34*(6), 26-38.

Belsky, J., Goode, M. K., & Most, R. K. (1980). Maternal stimulation and infant exploratory competence: Cross-sectional, correlational, and experimental analyses. *Child Development, 51*, 1168-1178.

Bourgeois, K. S., Khawar, A. W., Neal, S. A., & Lockman, J. J. (2005). Infant manual exploration of objects, surfaces, and their interrelations. *Infancy, 8*, 233-252.

Denison, S., & Xu, F. (2014). The origins of probabilistic inference in human infants. *Cognition, 130*(3), 335-347.

Denison, S., & Xu, F. (2019). Infant statisticians: The origins of reasoning under uncertainty. *Perspectives on Psychological Science, 14*(4), 499-509.

Dubey, R., Agrawal, P., Pathak, D., Griffiths, T. L., & Efros, A. A. (2018). Investigating human priors for playing video games. *arXiv preprint arXiv:1802.10217*.

Gaver, W. W. (1991). Technology affordances. In S. P. Robertson, G. Olson & J. Olson (Eds.), *Proceedings of the CHI'91 SIGCHI Conference on Human Factors in Computing Systems* (pp. 79-84). New York: ACM Press.

Gershman, S. J. (2018). Deconstructing the human algorithms for exploration. *Cognition, 173*, 34-42.

Gerson, S. A., & Woodward, A. L. (2013). Learning from their own actions: The unique effect of producing actions on infants' action understanding. *Child Development, 85*, 264-267.

Gopnik, A. (2012). Scientific thinking in young children: Theoretical advances, empirical research, and policy implications. *Science, 337*(6102), 1623-1627.

Gopnik, A. (2020). Childhood as a solution to explore–exploit tensions. *Philosophical Transactions of the Royal Society B, 375*(1803), 20190502.

Gopnik, A., Meltzoff, A. N., & Kuhl, P. K. (1999). *The scientist in the crib: Minds, brains, and how children learn*. Farfield, NJ: William Morrow & Co.

Gottlieb, J., Oudeyer, P. Y., Lopes, M., & Baranes, A. (2013). Information-seeking, curiosity, and attention: Computational and neural mechanisms. *Trends in Cognitive Sciences, 17*, 585-593.

Gweon, H., Tenenbaum, J. B., & Schulz, L. E. (2010). Infants consider both the sample and the sampling process in inductive generalization. *Proceedings of the National Academy of Sciences, 107*(20), 9066-9071.

Hartson, H. R. (2003). Cognitive, physical, sensory, and functional affordances in interaction design. *Behavior and Information Technology, 22*, 315-338.

Ishak, S., Franchak, J. M., & Adolph, K. E. (2014). Perception-action development from infants to adults: Perceiving affordances for reaching through openings. *Journal of Experimental Child Psychology, 117*, 92-105.

Jung, W. P., Kahrs, B. A., & Lockman, J. J. (2015). Manual action, fitting, and spatial planning: Relating objects by young children. *Cognition, 134*, 128-139.

Jung, W. P., Kahrs, B. A., & Lockman, J. J. (2018). Fitting handled objects into apertures by 17- to 36-month-old children: The dynamics of spatial coordination. *Developmental Psychology, 54*, 228-239.

Kahrs, B. A., Jung, W. P., & Lockman, J. J. (2012). What is the role of infant banging in the development of tool use? *Experimental Brain Research, 218*, 315-320.

Kosoy, E., Belyi, M., Snell, C., Lake, B., Tenenbaum, J., & Gopnik, A. (2021). *The Omniglot Jr. challenge; Can a model achieve child-level character generation and classification?* Paper presented at the Proceedings of the Annual Meeting of the Cognitive Science Society.

Kosoy, E., Collins, J., Chan, D. M., Huang, S., Pathak, D., Agrawal, P., et al. (2020). Exploring exploration: Comparing children with rl agents in unified environments. *arXiv preprint arXiv:2005.02880*.

Kushnir, T., & Gopnik, A. (2005). Young children infer causal strength from probabilities and interventions. *Psychological science, 16*(9), 678-683.

Legare, C. H. (2012). Exploring explanation: Explaining inconsistent evidence informs exploratory, hypothesis-testing behavior in young children. *Child development, 83*(1), 173-185.

Lockman, J. J. (2000). A perception-action perspective on tool use development. *Child Development, 71*, 137-144.

Lockman, J. J., Ashmead, D. H., & Bushnell, E. W. (1984). The development of anticipatory hand orientation during infancy. *Journal of Experimental Child Psychology, 37*, 176-186.

Lockman, J. J., & Kahrs, B. A. (2017). New insights into the development of human tool use. *Current Directions in Psychological Science, 26*, 330-334.

Lucas, C. G., Bridgers, S., Griffiths, T. L., & Gopnik, A. (2014). When children are better (or at least more open-minded) learners than adults: Developmental differences in learning the forms of causal relationships. *Cognition, 131*(2), 284-299.

McCarty, M. E., Clifton, R. K., & Collard, R. R. (2001). The beginnings of tool use by infants and toddlers. *Infancy, 2*, 233-256.

Meder, B., Wu, C. M., Schulz, E., & Ruggeri, A. (2021). Development of directed and random exploration in children. *Developmental science, 24*(4), e13095.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., et al. (2015). Human-level control through deep reinforcement learning. *nature, 518*(7540), 529-533.

Mousavi, S. S., Schukat, M., & Howley, E. (2016). *Deep reinforcement learning: an overview.* Paper presented at the Proceedings of SAI Intelligent Systems Conference.

Newell, A., & Simon, H. A. (1972). *Human problem solving*. Englewood Cliffs, NJ: Prentice Hall.

Norman, D. A. (1999). Affordance, conventions, and design. *Interactions, 6*, 38-43.

Norman, D. A. (2013). *The design of everyday things, revised and expanded*. New York: Basic Books.

Ossmy, O., Han, D., Cheng, M., Kaplan, B. E., & Adolph, K. E. (2020). Look before you fit: The real-time planning cascade in children and adults. *Journal of Experimental Child Psychology, 189*, 104696.

Ossmy, O., Hoch, J. E., MacAlpine, P., Hasan, S., Stone, P., & Adolph, K. E. (2018). Variety wins: Soccer-playing robots and infant walking. *Frontiers in Neurorobotics, 12*, 19.

Oudeyer, P. Y., Baranes, A., & Kaplan, F. (2013). Intrinsically motivated learning of real world sensorimotor skills with developmental constraints. In G.

Baldassarre & M. Mirolli (Eds.), *Intrinsically motivated learning in natural and artificial systems* (pp. 303-365). Berlin, Germany: Springer-Verlag.

Palmer, C. F. (1989). The discriminating nature of infants' exploratory actions. *Developmental Psychology, 25*, 885-893.

Pelz, M., & Kidd, C. (2020). The elaboration of exploratory play. *Philosophical Transactions of the Royal Society B, 375*(1803), 20190503.

Rachwani, J., Kaplan, B. E., Tamis-LeMonda, C. S., & Adolph, K. E. (2021). Children's use of everyday artifacts: Learning the hidden affordance of zipping. *Developmental Psychobiology, 63*(4), 793-799.

Rachwani, J., Tamis-LeMonda, C. S., Lockman, J. J., Karasik, L. B., & Adolph, K. E. (2020). Learning the designed actions of everyday objects. *Journal of Experimental Psychology: General, 149*, 67-78.

Ruggeri, A., Lombrozo, T., Griffiths, T. L., & Xu, F. (2016). Sources of developmental change in the efficiency of information search. *Developmental psychology, 52*(12), 2159.

Ruggeri, A., Xu, F., & Lombrozo, T. (2019). Effects of explanation on children's question asking. *Cognition, 191*, 103966.

Schulz, E., & Gershman, S. J. (2019). The algorithmic architecture of exploration in the human brain. *Current opinion in neurobiology, 55*, 7-14.

Schulz, E., Wu, C. M., Ruggeri, A., & Meder, B. (2019). Searching for rewards like a child means less generalization and more directed exploration. *Psychological science, 30*(11), 1561-1572.

Schulz, L. (2012). The origins of inquiry: Inductive inference and exploration in early childhood. *Trends in cognitive sciences, 16*(7), 382-389.

Schulz, L. E., & Bonawitz, E. B. (2007). Serious fun: Preschoolers engage in more exploratory play when evidence is confounded. *Developmental Psychology, 43*, 1045-1050.

Seiver, E., Gopnik, A., & Goodman, N. D. (2013). Did she jump because she was the big sister or because the trampoline was safe? Causal inference and the development of social attribution. *Child development, 84*(2), 443-454.

Sommerville, J. A., Woodward, A. L., & Needham, A. W. (2005). Action experience alters 3-month-old infants' perception of others' actions. *Cognition, 96*, B1-B11.

Soska, K. C., & Adolph, K. E. (2014). Postural position constrains multimodal object exploration in infants. *Infancy, 19*, 138-161.

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*: MIT press.

Woodward, A. L., Sommerville, J. A., & Guajardo, J. J. (2001). How infants make sense of intentional action. *Intentions and intentionality: Foundations of social cognition*, 149-169.

Supplementary Material

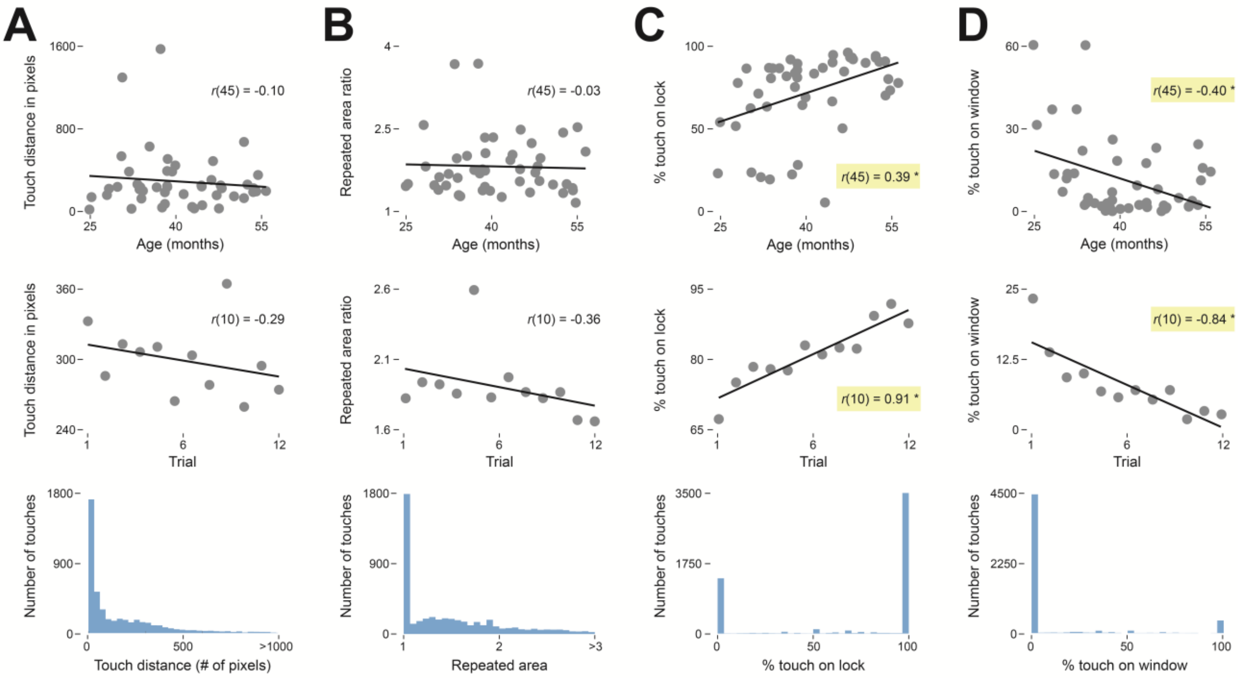

Figure S1. Touch measures. We used 4 touch measures to label touch area (lock, window, other; see examples in Figure 4) and touch action (press, repetitive slide, short slide, long slide; see examples in Figure 4)—**(A)** touch distance, **(B)** repeated area, **(C)** % touch on lock, and **(D)** % touch on window. First row shows each measure by age, second row shows each measure by trial number, and third row shows the distribution of each measure over the entire dataset.

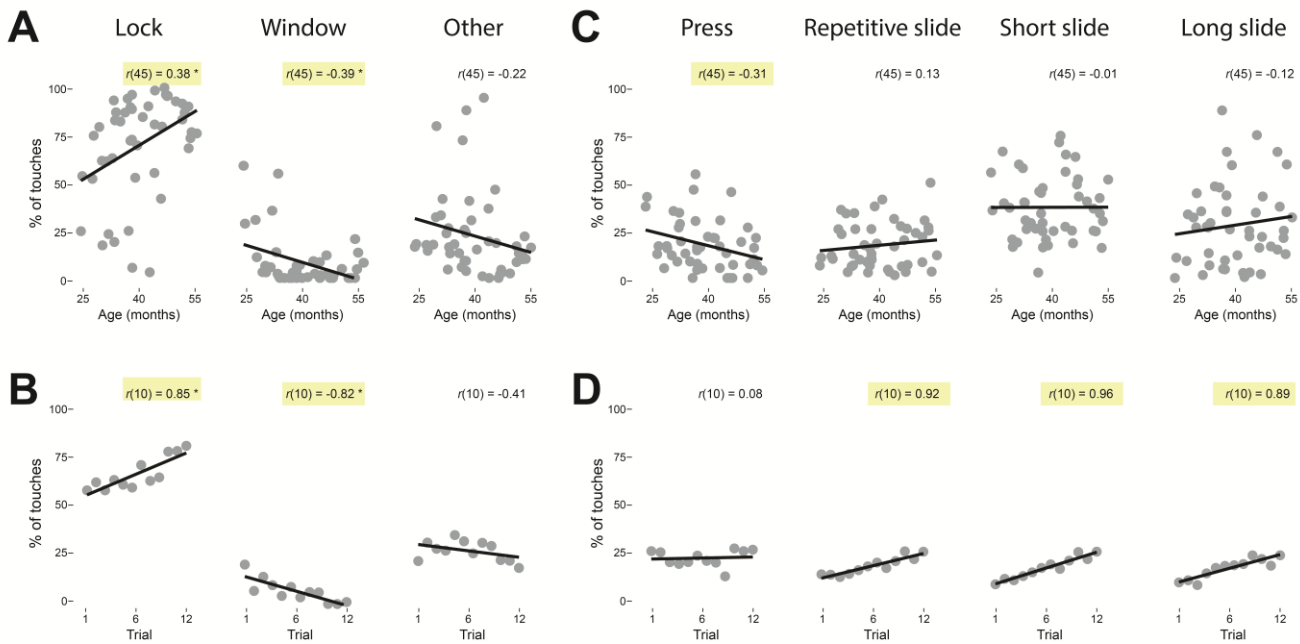

Figure S2. Touch types by age and trial number. The percent of touches in each area (lock, window, other; see Figure 4) as a function of **(A)** age and **(B)** trial number. Similarly, the percent of touches for each action (press, repetitive slide, short slide, and long slide; see Figure 4) as a function of **(C)** age and **(D)** trial number.

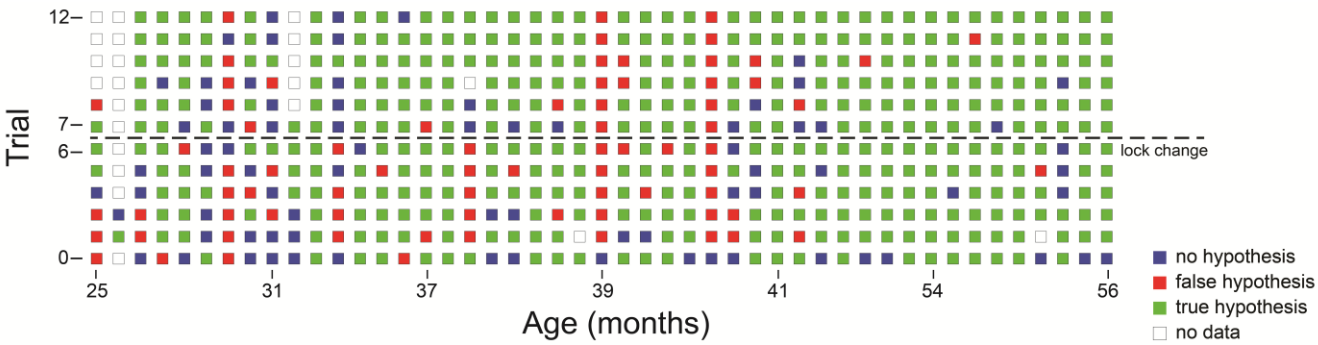

Figure S3. Area hypotheses. Squares indicate no area hypothesis (blue), false area hypothesis (red), true area hypothesis (green), or no data (empty) for each child and each trial. See correlation of area hypotheses with age and experience in Figures 6 and 7 respectively.

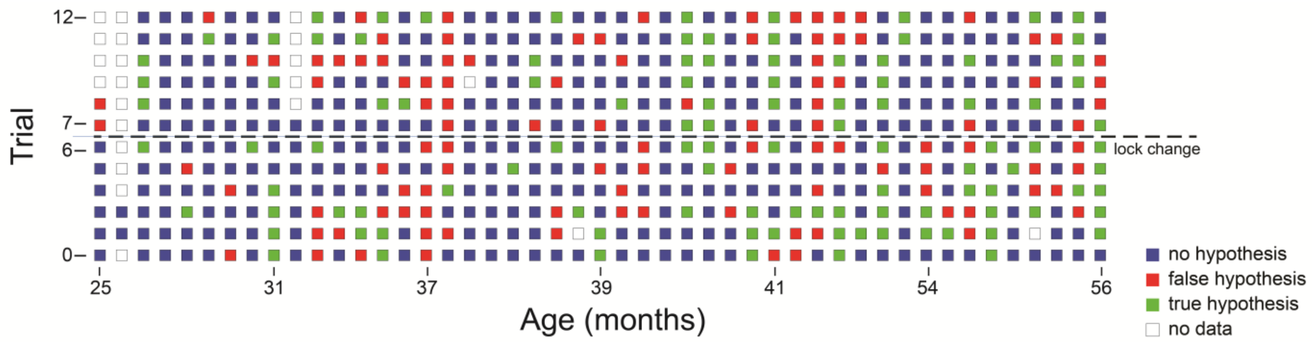

Figure S4. Action hypotheses. Squares indicate no action hypothesis (blue), false action hypothesis (red), true action hypothesis (green), or no data (empty) for each child and each trial. See correlation of action hypotheses with age and experience in Figures 6 and 7 respectively.

Table S1. Definition of touch area and action according to touch measures.

	Label	distance	repeated area	on lock	on window
Area	lock	-	-	> 90	> 90
	window	-	-	<= 90	<= 90
	other	-	-	<= 90	<= 90
Action	press	= 1	-	-	-
	repetitive slide	> 1	> 1.2	-	-
	short slide	> 1 and < 256	< 1.2	-	-
	long slide	> 256	< 1.2	-	-

*Note 256 = the length of the lock