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Children show limited movement repertoire when learning a novel motor skill

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Abstract

Examining age differences in motor learning using real-world tasks is often problematic due to task novelty and biomechanical confounds. Here, we investigated how children and adults acquire a novel motor skill in a virtual environment. Participants of three different age groups (9-year-olds, 12-year-olds, and adults) learned to use their upper body movements to control a cursor on a computer screen. Results showed that 9-year-old and 12-year-old children showed poorer ability to control the cursor at the end of practice. Critically, when we investigated the movement coordination, we found that the lower task performance of children was associated with limited exploration of their movement repertoire. These results reveal the critical role of motor exploration in understanding developmental differences in motor learning.

RESEARCH HIGHLIGHTS

- Motor exploration is a critical part of motor learning—yet developmental differences in motor exploration are not well understood.
- We used a novel paradigm to examine motor learning and exploration in three age groups: 9-year-olds, 12-year-olds and young adults (18–35 years).
- Children showed lower task performance compared to young adults even when the task was designed to minimize biomechanical constraints.
- Lower task performance was associated with limited exploration of movement repertoire during learning.

1 | INTRODUCTION

Despite the popular belief that children are better at learning motor skills compared to adults, there is a large body of evidence documenting poorer performance and learning in children relative to adults (Lukacs & Kemeny, 2015; K.M. Thomas et al., 2004; Wade, 1976). Movements in children are generally slower, less smooth and show increased variability (Bo, Bastian, Contreras-Vidal, Kagerer, & Clark, 2008; Yan, Thomas, Stelmach, & Thomas, 2000). These age-related differences have been mainly attributed to the fact that the nervous system of children is still developing both structurally and functionally, and therefore impacts critical learning mechanisms such as information processing (Sullivan, Kantak, & Burtner, 2008; J.R. Thomas, 1980), and memory (Karmiloff-Smith, 1995; K.M. Thomas et al., 2004).

However, two important factors need to be considered when examining differences between children and adults in motor learning. The first issue is task novelty—typical motor learning tasks used for investigating developmental differences (such as key pressing or reaching paradigms) can be classified as scaling tasks in that they involve the adaptation or re-parameterization of already well-learned coordination patterns (Newell, 1991). Using these tasks potentially creates a bias in favor of adults simply because of their extensive prior experience with these coordination patterns. To overcome this confound, recent studies have used tasks which require the acquisition of a novel spatiotemporal coordination pattern—such as juggling (Voelcker-Rehage & Willimczik, 2006) or split-belt walking (Vasudevan, Torres-Oviedo, Morton, Yang, & Bastian, 2011). However, even in these novel tasks, there is a second issue that could potentially confound results—development results in changes not only to the nervous system but also in biomechanical factors such as body mass, size, and strength. For example, although children show increased movement variability compared to adults when adapting the same force field, the higher variability may simply be a consequence of children operating at a higher percentage of their maximum force production capability (Takahashi et al., 2003). Although attempts have been made to account for some of these differences by adapting the task for children—for example, by using lower walking speeds during split-belt walking (Vasudevan et al., 2011), it becomes difficult to directly compare adults and children in real-world physical tasks especially if they require movements of large body segments because biomechanical factors play a larger role in performance. Therefore in order to characterize developmental differences in motor learning, it is critical to use a paradigm that minimizes confounds due to task novelty and biomechanics.

In view of these two confounds, we used a novel virtual task based on the body–machine interface paradigm (Casadio, Ranganathan, & Mussa-Ivaldi, 2012; Mosier, Scheidt, Acosta, & Mussa-Ivaldi, 2005; Ranganathan, Adewuyi, & Mussa-Ivaldi, 2013). In simple terms, a body–machine interface transforms body movements into commands for the control of a device—for example, the position of a screen cursor (Figure 1). This paradigm allows for a more accurate comparison of learning between children and adults because: (i) the task can be made equally novel to children and adults since the experimenter is in control of how the movements map to the device commands; and (ii) the task can be used to minimize differences in motor performance due to biomechanical factors since it is completely virtual and can be customized to each individual (to account for differences in body size, range of motion, etc.). Finally, an important feature is that the dimensionality of the body space can be made higher than the dimensionality of the task space, meaning that there is "redundancy" or multiple solutions to achieve the goal (Bernstein, 1967). This allows greater insight into age-related differences in motor learning because in addition to quantifying learning in terms of improvement in the task outcome, we can also examine how the task was achieved in terms of the coordination between the degrees of freedom in the body.

In this study, we used this novel paradigm to address the issue of motor exploration—a topic that has received very little attention especially with respect to development. Motor exploration is the ability to generate different movement patterns during learning, and this variability has been considered critical to learning both from dynamical systems theory (Davids, Bennett, & Newell, 2006) and reinforcement learning (Sutton & Barto, 1998). In both views, motor exploration is considered essential to being able to move out of existing solutions and find new solutions (Thelen, 1995). Studies on infants have demonstrated exploratory activity when transitioning to a new behavior like reaching (Thelen & Corbetta, 1994), where exploratory movements such as spontaneous arm flapping are gradually sculpted into smooth goal-directed reaching movements. In adults, increased movement variability during learning has been associated with faster learning (Wu, Miyamoto, Gonzalez Castro, Olveczky, & Smith, 2014), and higher task performance (Teo, Swayne, Cheeran, Greenwood, & Rothwell, 2011), and it has been shown that this variability during learning can also be modulated by reward (Pekny, Izawa, & Shadmehr, 2015). However, there is also evidence that too much variability can also affect learning adversely (He et al., 2016; Ranganathan & Newell, 2013; Therrien, Wolpert, & Bastian, 2015), suggesting that not all movement variability may be related to exploration. Therefore, while motor exploration plays a central role in motor learning, there is currently limited understanding of how motor exploration impacts learning in children.

Here, we examined how children and adults learned a novel motor task, where we could quantify both task performance and motor exploration. Based on previous research, we hypothesized that children would show lower task performance at the end of practice compared to adults. and we examined whether the these differences in task performance could be attributed to differences in motor exploration.

2 | METHODS

2.1 | Participants

A total of 45 participants volunteered for the study. We tested three age groups: 9-year-olds (M = 9.57 years, SD = 0.94 years, n = 13, 5 females), 12-year-olds (M = 12.17 years, SD = 0.68 years, n = 12, 2 females), and adults (M = 24.94 years, SD = 5.36 years, n = 20, 10 females). Our choice of the age groups was based on prior studies on learning across the lifespan (Lukacs & Kemeny, 2015; Voelcker-Rehage & Willimczik, 2006) that show that task performance increases with age from about 9 years, and reaches adult-like performance around 15 years. Moreover, because this is a virtual task, we had a concern that very young children (< 6 years old) may not be able to sufficiently understand the task instructions to perform the task. Informed consent (including parental consent when needed) was obtained and procedures were approved by Michigan State University Human Research Protection Program.

2.2 | Experimental set-up and design

Participants sat in front a 23″ (58.4 cm) computer monitor and were instructed to move their upper body to control a cursor on the computer monitor. A customized vest was put on the participant with Velcro loops around the shoulder area. Four wireless inertial measurement units (IMUs) (3-space, YEI Technology, Ohio, USA) were attached to the vest using Velcro hooks (Figure 1) and captured scapular retraction, protraction, elevation and depression (Farshchiansadegh et al., 2014). The four sensors were attached to the anterior and posterior end of the acromioclavicular joint on both the left and right sides of the body (Figure 1). We only used the signals corresponding to the roll and pitch angles from each IMU sensor since the yaw angles were relatively noisy. This resulted in an 8-D signal (4 IMU sensors × 2 signals/sensor) which constituted the "body space".

2.3 | Mapping body motions to cursor position

We used linear mapping to convert the 8-dimensional body space (h) into the 2-D task space, which was the cursor position (p). The mapping used was given by $p = A\,h + p_0$, where A refers to the map and p_0 is an offset term. (Farshchiansadegh et al., 2014). To determine the map A, we used a calibration procedure similar to previous studies (Farshchiansadegh et al., 2014; Ranganathan et al., 2013). During the calibration, participants performed free exploratory movements for 60 s where they were asked to explore different motions that they

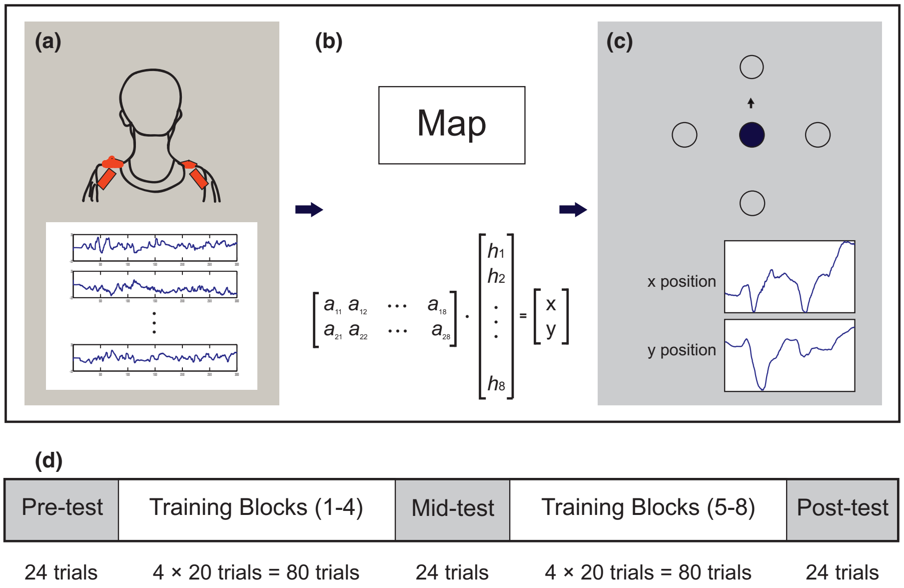

FIGURE 1 Schematic of a body–machine interface. (a) Inertial measurement units (IMUs) are attached to the upper body (near the shoulder) of a participant which provide orientation information. (b) The interface uses a map A that transforms the IMU signals *h* into the position of a screen cursor *p* using a linear mapping as shown. (c) The x-y position of the cursor is displayed to the participant on a screen. During the experiment, the goal of the participants is to move the cursor to different targets displayed on the screen. The lower panel shows how the x-y positions of the cursor vary with time as the IMU signals change their values. (d) Experimental protocol showing the “test” blocks (pre-test, mid-test and post-test) which required reaches to eight targets on the screen, and the eight “training” blocks which required reaching for four targets on the screen

could perform with the upper body, while maintaining a comfortable range of motion. We then performed principal component analysis (PCA) on the calibration data and extracted the first two components. These two vectors of component coefficients were scaled by a gain factor (which was equal to the reciprocal of the square root of the respective eigen value) to make the movements along both axes comparable in difficulty (having equal variance). The two scaled vectors were then used to form the matrix *A*. The offset p_0 was set so that the average posture during calibration (which was close to the resting posture) resulted in the cursor being in the center of the computer screen.

It is critical to note two important features of the task—(i) the signals from the IMUs captured only angles in the upper body (i.e., shoulder and torso), and therefore the task was not influenced by developmental differences in the length of body segments (such as arm length), (ii) calibration was done at an individual level so that each participant could successfully perform the task—this meant that differences in range of motion and sensor placement also did not affect participants’ ability to perform the task. This approach to scaling the task based on the participant’s own movement repertoire is similar to the approach of scaling the task differently for children—for example, by changing walking speed (Vasudevan et al., 2011), or in force production experiments where targets are scaled to the maximum force production ability (Deutsch & Newell, 2001).

2.4 | Cursor control task

Participants had to move their shoulders and torso (where the sensors were placed) in order to control a cursor on the computer screen to perform a virtual center-out reaching task. Participants moved the cursor from the home target (r = 2.2 cm, in the center) to one of a number of peripheral targets presented at a distance of 11.5 cm, and then returned back to the home target. The peripheral targets were presented in a random sequence. Each trial started when the home target showed up for 500ms followed by the presentation of a peripheral target. Participants were instructed to move the cursor to the target as fast and as close to the center of the target as possible. The task also required the participant to keep the cursor inside the target circle for 500ms before they returned to the home target.

Participants performed two types of blocks: there were eight “training” blocks in which they reached for 4 peripheral targets in the cardinal directions five times each (for a total of 20 trials), and three “test” blocks (pre-, mid- and post-test) in which they reached for eight peripheral targets three times (for a total of 24 trials). Direct comparisons between groups were focused on the test blocks, and the additional targets placed along diagonal directions in the test blocks were designed to test whether the learning in the training sessions generalized to unpracticed directions. The experimental set-up and protocol is shown in Figure 1.

3 | DATA ANALYSIS

All analyses were performed only on the outward movements—that is, when the participant moved from the home target toward the peripheral targets. We selected only the outward movements because the return movement to the home target involved coming back to the same initial posture, which was generally easier to do (and therefore required less exploration than the outward movements). We divided the data analysis metrics into two categories: task performance and coordination.

3.1 | Task performance

We quantified task performance using the movement time, and the normalized path length (which measured the straightness of the path taken). The cursor control task was designed so that each trial stopped only when the target was reached, at which point the subsequent target was presented. Because all targets were at a fixed distance from the home target, we used movement time as the primary measure of task performance (spatial accuracy was controlled for because all reaches eventually reached the target). In addition, even though this was not an explicit instruction to the participants, we used the straightness of the path (normalized path length) as a secondary measure of task performance to measure the degree of control they had over the cursor. The rationale for this metric is that there is a tendency for participants to move in straight lines when learning novel reaching tasks (Mosier et al., 2005; Shadmehr & Mussa-Ivaldi, 1994). Moreover, because the targets were arranged in a circle around the home position, moving the cursor in straighter paths would indicate that participants are able to control the x- and y- motion of the cursor both independently (when the targets were in the cardinal directions) and simultaneously (when the targets were in the diagonal directions). As a result, the normalized path length also allowed us to understand differences in movement time better—longer movement times could be due to convoluted cursor trajectories indicating poor control of the cursor (high normalized path length), or making slow but straight movements (low normalized path length).

Movement time was calculated from the time that the cursor left the home target to the time that it reached and stayed inside the target for the subsequent 500 ms. Normalized path length between two targets was defined as the actual distance traveled by the cursor divided by the straight line distance between the targets (i.e., reaching to a target in a straight line without any movement reversals would result in a normalized path length of 1). In addition to these two metrics used to measure learning, we also computed the peak speed of the cursor during the movement to examine whether differences in movement time were due to differences in the ability to move at high velocity.

3.2 | Coordination

For assessing the coordination of the upper body, we used principal components analysis PCA (Daffertshofer, Lamoth, Meijer, & Beek, 2004). Even though a single reach required movement along only one direction, the cursor control task over an entire training or test block required the participant to control the cursor in a 2-D space, requiring at least two distinct coordination patterns. We therefore analyzed the time series of the eight signals in each block using PCA and computed the percent of variance accounted for (VAF) by the first two principal components to investigate the degree of exploration in participants' body movements when learning the task. We used the covariance matrix to perform the PCA (which preserves the amplitude information in the signals).

To analyze the degree of motor exploration, we used the relative distribution of variance along the first two PCs (rather than the total movement variability) as an index of motor exploration because we were interested in how participants explored between different coordination patterns (and not the variation within a single coordination pattern). We quantified this exploration using the variance aspect ratio—that is, the ratio of variance along PC2 to that along PC1—a larger variance ratio indicates greater exploration along both coordination patterns. The ratio along two orthogonal directions has been used as a measure of motor coordination in the uncontrolled manifold hypothesis (Scholz & Schoner, 1999), and has also recently been used to quantify exploration (Ranganathan, Wieser, Mosier, Mussa-Ivaldi, & Scheidt, 2014).

For example, if the two PCs both had almost similar amount of VAF (say 40% in PC1 and 30% in PC2, variance aspect ratio = 0.75), that indicates that participants were able to successfully explore along two coordination patterns. On the other hand, if the distribution of VAF was skewed highly toward PC1 (say 60% in PC1 and 10% in PC2, variance aspect ratio = 0.16), this indicated that participants were relatively "stuck" in one coordination pattern and only showed limited exploration of the second.

4 | STATISTICAL ANALYSIS

To examine changes with learning, we analyzed only the pre-test, mid-test and post-test (i.e., the training blocks were not included for statistical analysis). The dependent variables were analyzed using a 3 × 3 (Block × Group) repeated measures ANOVA. Block (Pre-test, mid-test, post-test) was the within-subjects factor, whereas Group (9 years,12 years, adult) was the between-subjects factor. Violations of sphericity were corrected using the Greenhouse-Geisser factor when applicable. To minimize the number of comparisons, post-hoc comparisons for group were examined using the Sidak correction only at the pre-test and post-test. Significance levels were set at $p < .05$.

5 | RESULTS

5.1 | Task performance

A sample of cursor paths in the pre-test and post-test from a representative participant in each of the age groups is shown in Figure 2. All groups decreased movement time with practice as indicated by a significant main effect of block, $F(1.04, 43.85) = 91.20$, $p < .001$ (Figure 3a). There was also an age-related effect indicated by a significant main effect of group, $F(2, 42) = 15.92$, $p < .001$, which was mediated by a significant Block × Group interaction, $F(2.09, 43.85) = 4.72$, $p = .013$. Post-hoc analysis of this interaction effect showed that at the pre-test, adults had significantly shorter movement times than 9-year-olds, and at the post-test, adults had shorter movement

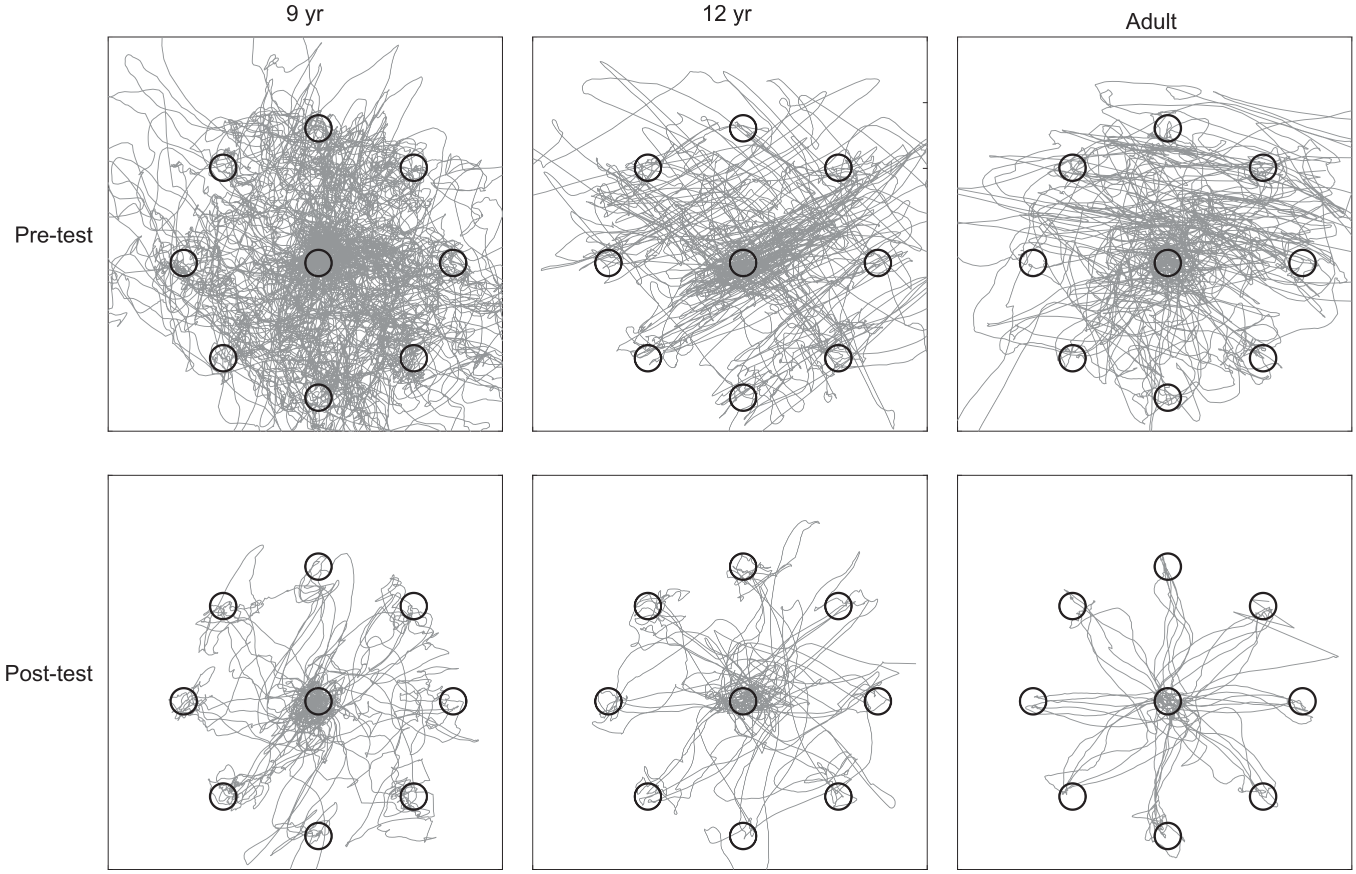

FIGURE 2 Cursor paths before and after learning from a typical participant in the three age groups. There is a clear effect of age, with straighter paths with increasing age, which were also associated with shorter movement times

times than both the 9-year-olds and the 12-year-olds (all *ps* <. 001). In addition, the 12-year-olds had shorter movement times than the 9-year-olds only at the post-test (*p* = .046).

Results were similar for analysis of the normalized path length (Figure 3b). All age groups showed smaller path lengths (i.e., straighter cursor paths) with practice—main effect of block, *F*(1.03, 43.42) = 44.29, *p* < .001. There was also a significant age-related effect indicated by a significant main effect of group, *F*(2, 42) = 9.60, *p* < .001, which was mediated by a significant Block × Group interaction, *F*(2.07, 43.42) = 4.25, *p* = .02. Post-hoc analysis of this interaction effect showed an ordinal interaction where both at the pre-test and post-test, adults showed significantly straighter paths than the 9-year-olds, but the magnitude of this difference decreased with practice (pre-test *p* = .004, post-test *p* < .001). The difference between 12-year-olds and adults and between 9- and 12-year-olds was not significant.

In addition, to rule out the possibility that the shorter movement times in adults were simply a consequence of adults being able to move with higher velocities, we also examined the peak speed of the cursor during the movement. Surprisingly, peak speed actually decreased with practice as indicated by a significant main effect of block, *F*(1.36, 57.05) = 35.06, *p* < .001. There was also an age-related difference indicated by a main effect of group, *F*(2, 42) = 5.94, *p* = .005, which was mediated by a significant Block × Group interaction, *F*(2.72, 57.05) = 3.11, *p* = .038. Analysis of the interaction indicated that at the pre-test, adults in fact had lower peak speeds than both 9-year-olds and 12-year-olds (*p* = .011 and *p* =.045), and this difference between the adults and the 9-year-olds was smaller but persisted at the post-test (*p* = .04). The peak speeds of the 12-year-olds were not significantly different from either the adults or the 9-year-olds at the post-test. These lower peak speeds seen in adults (along with the shorter path lengths) show that the shorter movement times were due to a better ability to control the cursor, and not due to a biomechanical advantage of being able to move faster.

5.2 | Coordination

There were also age-related and practice-related changes in coordination strategies. For the VAF-PC1, there was main effect of block, *F*(2, 84) = 7.36, *p* = .001 (Figure 3c). There was also a significant main effect of group, *F*(2, 42) = 6.19, *p* = .004, which was mediated by a significant Block × Group interaction, *F*(4, 84) = 2.57, *p* = .043. Post-hoc analysis of the main effect of group indicated that adults had lower VAF- PC1 than the 9- and 12-year-olds (*ps* < .01)—however, the interaction was due to the fact that trends with practice in the groups were different: 12-year-olds and adults showed an increase in

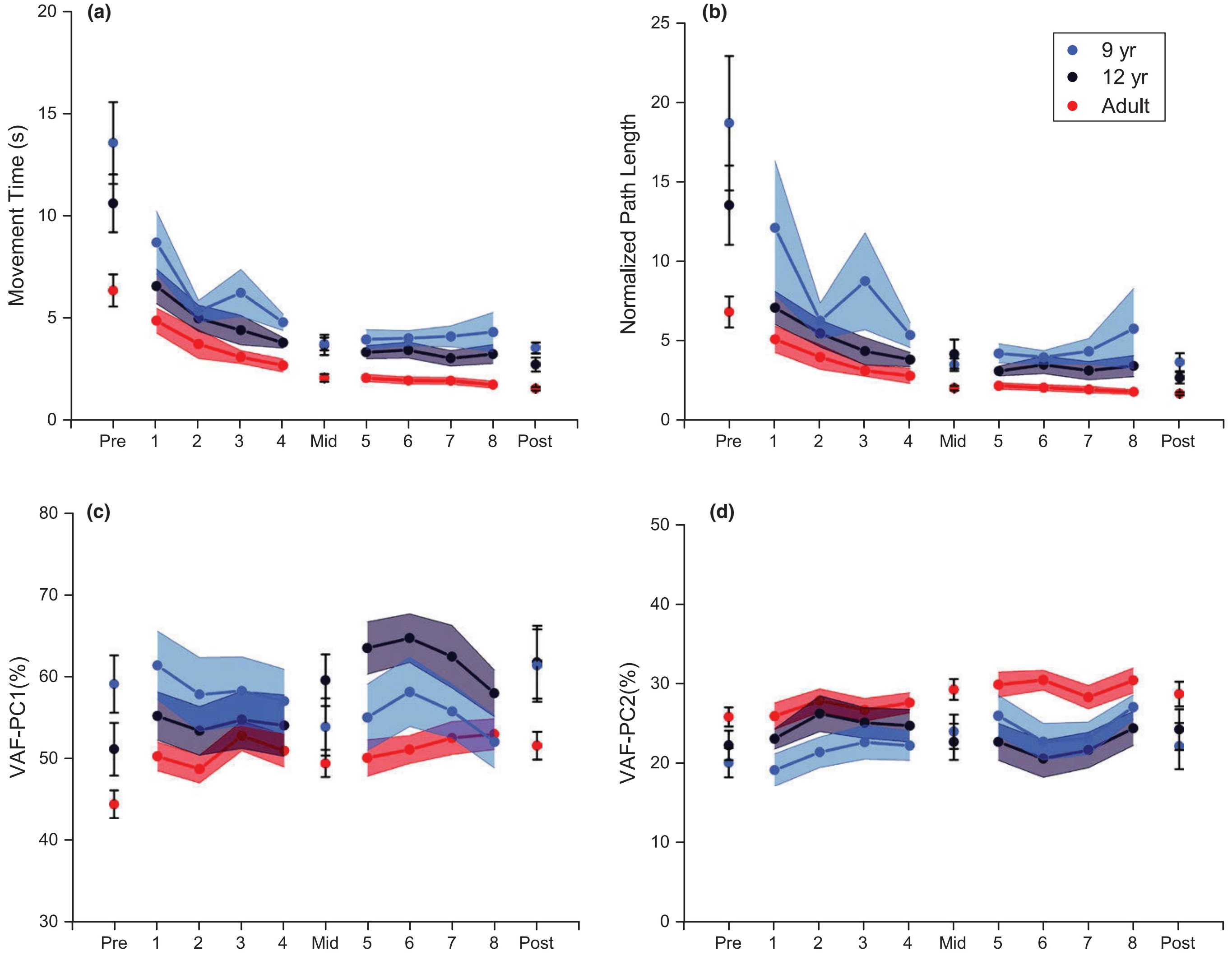

FIGURE 3 (a) Movement time, and (b) path length as a function of practice in the three age groups. There is a clear developmental trend with faster movement times and straighter paths with increasing age. Variance accounted for (VAF) by the first two principal components (c) PC1, and (d) PC2 as a function of practice in the three age groups. Children tend to have much greater variance along PC1 relative to PC2, indicating a tendency to get "stuck" in one coordination pattern. Error bands represent one standard error

VAF-PC1 with training from pre-test to post-test (p = .014 for adults, p = .005 for 12-year-olds), whereas 9-year-olds tended to show a consistently high value that did not change much with practice (p > .05). For VAF-PC2, there was only a significant main effect of Group, $F(2, 42)$ = 5.00, p = .011 (Figure 3d). Post-hoc analysis revealed that adults had higher VAF-PC2 than 9-year-olds (p = .019).

To rule out the possibility that these differences in VAF-PC1 and VAF-PC2 were either due to intrinsic biomechanical differences in the movement repertoire of the upper body (i.e., the ability to make different types of movements) or an artifact of how children and adults moved during the calibration (which would affect the mapping), we compared the VAF-PC1 and VAF-PC2 during the calibration phase (where participants explored moving their upper body but there was no cursor to control). We found no statistical differences between the age groups (VAF-PC1: $F(2, 42)$ = .845, p = .437; VAF-PC2: $F(2, 42)$ = .335, p = .718), which indicates that the differences we found during the task were specifically related to learning how to control the cursor.

Finally, to further examine the hypothesis that the restricted exploration of the movement repertoire led to lower task performance, we computed a correlation between the aspect ratio (defined as the square root of the ratio of variance in PC2 to PC1) against the movement time during the post-test (Figure 4). The analysis showed a significant correlation r = −0.42, p = .004, CI = [−0.64, −0.12]. To examine if the correlation was influenced by outliers, we also computed a robust correlation measure—the 20% bend-correlation (Pernet, Wilcox, & Rousselet, 2013), which was also significant, r = −0.33, p = .025, CI = [−0.62, −0.04].

6 | DISCUSSION

One of the key issues in the study of developmental science is to understand the nature of developmental change (Adolph, Robinson, Young, & Gill-Alvarez, 2008). Here, we utilized a novel task paradigm

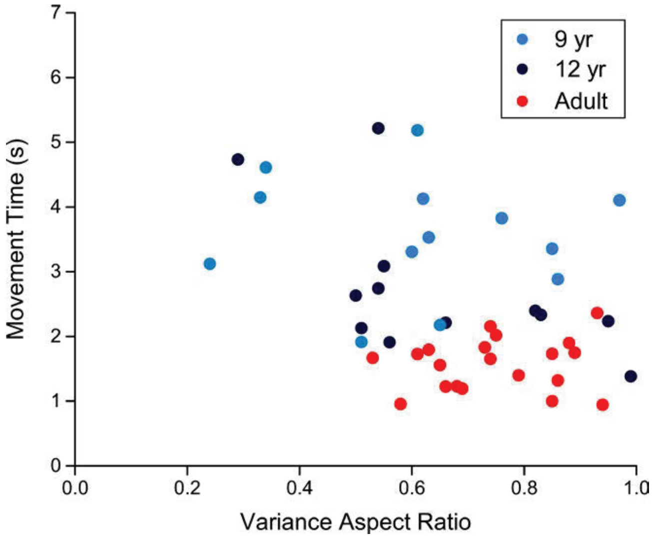

FIGURE 4 Scatterplot of variance aspect ratio (a measure of exploration) and the movement time in the post-test for the three age groups. Reduced exploration of the movement repertoire is associated with lower task performance in learning the novel task

to address the issue of how the ability to learn a novel motor skill changes during early development (Lukacs & Kemeny, 2015; Voelcker-Rehage & Willimczik, 2006). In spite of minimizing confounds due to task familiarity and biomechanics, the analysis of task performance showed that the children did not perform as well as the adults at the end of practice. Children showed longer movement times that were also associated with longer path lengths (and higher peak velocities), indicating that these differences were due to a poorer ability to control the cursor, and were unlikely to be biomechanical in nature. Critically, when we examined the coordination underlying performance, we found evidence of age-related differences in motor exploration—younger children restricted exploration mostly along the first principal component (i.e., they were "stuck" in one coordination pattern), indicating reduced exploration of the movement repertoire. These age differences in exploration were not only evident at the group level, but we also found that overall, individuals with reduced exploration tended to show worse task performance (longer movement times). Although there is an argument that the change scores in the movement time (i.e., the difference from pre-test to post-test) was in fact greater in children, this was primarily due to children having significantly longer movement times at the pre-test, and our focus in the current study was to relate the degree of motor exploration directly to the task performance after learning (i.e., on the post-test).

Variability and exploration has been widely acknowledged as a critical feature of motor control and development (Davids et al., 2006; Hadders-Algra, 2010; Stergiou, Harbourne, & Cavanaugh, 2006). Although several theoretical perspectives such as dynamical systems theory (Kelso, 1995) and reinforcement learning (Sutton & Barto, 1998; Wu et al., 2014) highlight the key role of variability and exploration in learning, the trajectory of how this exploration evolves with development has been difficult to study experimentally in multiple degrees of freedom tasks. While several studies have documented higher variability in children (Deutsch & Newell, 2001; Yan et al., 2000), here we found that, perhaps counterintuitively, children show limited movement repertoire when learning a novel motor task. Importantly, the reduced motor exploration in children did not seem to be biomechanical in nature since the calibration phase (where participants did not have to control a cursor) indicated no age-related differences. Therefore, this might be a strategy adopted by the children when learning this novel task involving the coordination of multiple degrees of freedom—analogous to the "freezing of degrees of freedom" stage (Bernstein, 1967). This stage posits that learners simplify the degrees of freedom problem by "freezing" certain degrees of freedom initially during learning. Although the original interpretation of freezing as a reduction in the amplitude of movement in certain joints been debated (Konczak, Vander Velden, & Jaeger, 2009; Newell & Vaillancourt, 2001), a broader interpretation that the learner can simplify coordination by limiting motor exploration is consistent with the results seen here. Interestingly, given that children have been shown to have faster motor memory stabilization (Adi-Japha, Badir, Dorfberger, & Karni, 2014), a longer time scale of learning may be required to examine whether this initial inflexibility is consolidated and persistent, or is ultimately replaced by greater exploration of the movement repertoire. However, the fact that children can be more variable (as observed in the trajectories) and yet show limited exploration of the movement repertoire highlights the fact that variability cannot be treated as a single construct, and has multiple distinct roles in learning (Ranganathan & Newell, 2013).

These results showing that performance in children is worse than adults support similar studies on motor learning in other contexts such as sequence learning (K.M. Thomas et al., 2004) and locomotor adaptation (Vasudevan et al., 2011). However, an important contribution of the current study was to use a novel task that minimizes confounds due to task familiarity and biomechanical differences between children and adults. Specifically, the paradigm used here more closely resembles motor learning (as opposed to adaptation) in that participants had to learn a relatively novel movement pattern which could be used be brought up and used in the appropriate context (Bastian, 2008). Although studies of motor adaptation have quantified differences between children and adults (Takahashi et al., 2003; Vasudevan et al., 2011), a critical difference is that in adaptation paradigms, in addition to using already well-learned movements (such as reaching or walking), there are typically no explicit task instructions regarding the main dependent variable used to measure adaptation. For example, participants are not explicitly instructed to reduce asymmetry during split-belt walking, or to move their hand in a straight path when reaching in force fields. This distinction is important because it means that age-related differences seen in adaptation tasks are not only attributable to differences in the *ability* to adapt, but may also reflect differences in sensitivity to deviations from the normal movement pattern (for e.g., children walking on a split-belt treadmill with different speeds may not be as sensitive to deviations from the symmetric walking coordination pattern as much as adults). On the other hand, in the current paradigm, participants were explicitly asked to reduce movement time (which is the primary dependent variable), and therefore the results are more likely to be representative of real-world learning tasks where the goal is to improve performance.

The current work highlights the role of age-related differences in motor exploration in learning a novel motor skill, and has implications for practice schedules. Although there is a long history of examining variable practice in both adults and children (for a review, see Van Rossum, 1990), recent studies have specifically examined the role of variability in terms of modifying exploration in motor learning both in adults (Ranganathan et al., 2014; Teo et al., 2011; Wu et al., 2014) as well as infants (Lee & Newell, 2013). The current results suggest that practice schedules that increase exploration of the movement repertoire (i.e., getting them to perform different coordination patterns) should facilitate performance on the task in children, rather than simply increasing variability within the same coordination pattern (Ranganathan & Newell, 2013). Testing these predictions in future experiments will provide greater insight into the causal role of exploration in learning and development, and how it may eventually translate to movement rehabilitation both in children and adults.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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