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RESEARCH ARTICLE

Online and offline contributions to motor learning change with practice, but are similar across development

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Abstract

Children show motor learning deficits relative to adults across a diverse range of tasks. One mechanism that has been proposed to underlie these differences is the contribution of online and offline components to overall learning; however, these tasks have almost focused exclusively on sequence learning paradigms which are characterized by performance gains in the offline phase. Here, we examined the role of online and offline learning in a novel motor task which was characterized by warm-up decrement, i.e., a performance loss, during the offline phase. In particular, using a relatively extended practice period, we examined if differences between children and adults persist across relatively long practice periods, and if the contribution of online and offline learning is affected by age and by practice itself. Two groups of children, 8–10 years and 11–13 years old, and one group of young adults ($N=30$, $n=10$/group) learned a novel task that required control of upper body movements to control a cursor on a screen. Participants learned the task over 5 days and we measured movement time as the primary task performance variable. Consistent with prior results, we found that 8–10 year olds had longer movement times compared to both 11–13 year olds and adults. We also found distinct changes in online and offline learning with practice; the amount of online learning decreased with practice, whereas offline learning was relatively stable across practice. However, there was no detectable effect of age group on either online or offline learning. These results suggest that age-related differences in learning among children 8–10 years old are persistent even after extended practice but are not necessarily accounted for by differences in online and offline learning.

Keywords Skill learning · Consolidation · Warm-up · Forgetting · Age

Introduction

Across a range of different tasks, children show deficits in motor learning relative to adults (Wade 1976; Thomas 1980). These deficits have been shown both in laboratory tasks such as reaching (Yan et al. 2000), visuomotor rotations (Ferrel-Chapus et al. 2002), sequence learning (Lukacs and Kemeny 2015), gait adaptation (Vasudevan et al. 2011), and in real-world tasks such as juggling (Voelcker-Rehage and Willimczik 2006). Importantly, these deficits are not attributable simply to differences in motor abilities such as strength or size because even in novel virtual tasks that minimize such differences, these deficits still persist (Lee et al. 2018; Ranganathan et al. 2019).

One potential mechanism to understand the basis of these differences is to examine the contribution of online vs. offline components to overall learning (Dayan and Cohen 2011). Online learning refers to change that occurs during practice whereas offline learning refers to change that occurs during a period of no practice. Although the timescales involved in earlier studies were of the order of days—i.e., online performance was measured within-day and offline performance was measured between-days (Doyon and Benali 2005), these have also been extended to shorter timescales—practice blocks in a single day (Du et al. 2016) and trials in a block (Bönstrup et al. 2019). Here, we specifically use the term 'change' in performance rather than 'improvement' because even though learning typically refers to improvement in performance, this does not always have to be the case. There is some evidence that these two mechanisms are impacted differently with development, although the findings seem to be both task- and timescale dependent. For example, in sequence learning, young children seem to

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rely more on offline learning, whereas adults seem to depend on online learning (Du et al. 2017). However, in an invented-letter drawing task, younger children seemed to have deficits in offline learning, as seen by deficits in long-term retention relative to adults (Julius and Adi-Japha 2015). In addition, studies examining the role of sleep during offline learning have also found differences with age; children show less implicit learning (i.e., learning of probabilities embedded in the sequence) during the offline phase compared to adults (Wilhelm et al. 2012b).

Moreover, there are two unaddressed issues that limit the generality of these findings. First, the majority of studies have used sequence learning as the experimental paradigm, which is characterized by a performance gain in the offline phase, i.e., performance after the rest interval is better than prior to the rest interval (Robertson et al. 2004; Walker and Stickgold 2006). However, this is not fully representative of motor learning in general, as there is extensive evidence in many tasks for the phenomenon of 'warm-up decrement' where there is a performance loss in the offline phase (Adams 1961; Nacson and Schmidt 1971; Stratton et al. 2007; Newell et al. 2009; Verhoeven and Newell 2018). Understanding how online and offline learning contribute in tasks where warm-up decrement occurs can expand the generality of the findings from sequence learning. Second, by typically using only a 24-h period for examining online and offline learning, most studies have examined only a single snapshot of these processes—i.e., there is only one measure of offline and online learning. Given that age differences in learning seem to depend to some extent on how well participants can initially acquire the skill (Wilhelm et al. 2012a; Krishnan et al. 2018) it is critical to also understand if the contribution of online and offline learning processes themselves change as a function of practice and development. Understanding the role of offline and online learning during development has implications not only for mechanistic insights into motor skill learning, but also potential practical implications in terms of how practice intervals must be spaced relative to rest intervals to optimize learning.

To address both these issues, we examined a virtual cursor control task using a body–machine interface over an extended period (i.e., 5 days of learning) in children and adults, focusing on the within-day/between-day timescale of learning. A feature of this task was that not only was it novel and minimized confounds due to size and strength differences between adults and children (Lee et al. 2018), but critically, in contrast to sequence learning, it is associated with a warm-up decrement. We examined two research questions: (1) do children show deficits in motor learning in this task relative to adults even after relatively extensive practice, and (2) how are the contribution of the offline and online components of learning in this task affected by both age and practice?

Methods

Participants

Thirty participants from three different age groups participated in the study ($n = 10$/group): 8–10 year olds (6 females, $M = 9.71$ years, SD = 0.99 years), 11–13 year olds (5 females, $M = 11.88$ years, SD = 1.01 years) and adults (5 females, M 21.24 years, SD = 1.13 years). Children were paid \$70 for their participation, and young adults (all college students) received extra course credit. Informed consent (including parental consent when needed) was obtained prior to participation and all procedures were approved by the Michigan State University Institutional Review Board. Although the two child groups are quite close in terms of age, the age groups for the current study were based on our prior study that showed reliable age differences in this task, and our pilot testing indicated that children 7 years or under could not reliably complete this task.

Experimental setup and design

The experimental methods and procedures were identical to our prior study (Lee et al. 2018) with the exception of the duration of practice. The novelty of the current study was the use of a multi-day protocol to examine online and offline changes in learning. The procedures are briefly summarized below.

Participants sat in front of a 23″ (58.4 cm) computer monitor and were instructed to move their upper body to control a screen cursor. Four wireless inertial measurement units (IMUs) (3-space, YEI Technology, Ohio USA) were attached to the anterior and posterior end of the acromioclavicular joint on both the left and right sides of the body. We only used the signals corresponding to the roll and pitch angles from each IMU sensor, resulting in an 8-D signal (4 IMU sensors × 2 signals/sensor) which constituted the 'body space'.

Mapping body motions to cursor position

We used a linear mapping to convert the 8-dimensional body space ($\mathbf{h}$) into the 2-D task space, which was the cursor position ($\mathbf{p}$). The mapping used was given by $\mathbf{p} = \mathbf{A}\ \mathbf{h} + \mathbf{p_0}$, where $\mathbf{A}$ refers to the map and $\mathbf{p_0}$ is an offset term. To determine the map A, we used a calibration procedure similar to previous studies (Farshchiansadegh et al. 2014). During the calibration, participants performed free exploratory movements for 60 s where they were asked to explore different motions that they 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 eigenvalue) to make the movements along both axes comparable in difficulty, and formed the two rows of the matrix **A**. The offset $\mathbf{p_0}$ 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. This procedure allowed the task to be customized to each individual, minimizing both sensor placement variations, and any variations due to biomechanical effects like range of motion.

Cursor control task

Participants had to move their shoulders and torso to control a cursor on the computer screen to perform a virtual center-out reaching task (Fig. 1). Participants moved the cursor from the home position ($r = 2.2$ cm, in the center) to one of a number of peripheral 'targets' (of same radius) presented at a distance of 11.5 cm, and then returned back to the home position. The peripheral targets were presented in a random sequence. Each trial started when the home position showed up for 500 ms 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 of the target circle for 500 ms before they returned to the home position. Each trial terminated only when the target was reached, and upon reaching the target and returning to the home position, the subsequent target was presented.

Participants performed two types of blocks: there were 8 training blocks in which they reached for 4 peripheral targets in the cardinal directions 5 times each—for a total of 20 trials, and 3 'test' blocks—pre-, mid- and post-test in which they reached for 8 peripheral targets (4 cardinal and 4 intercardinal) 3 times for a total of 24 trials. The sequence in which these blocks were performed was: pre-test, training blocks 1–4, mid-test, training blocks 5–8 and the post-test at the end. Within each block, targets were presented in pseudorandom order with the constraint that all targets had to be

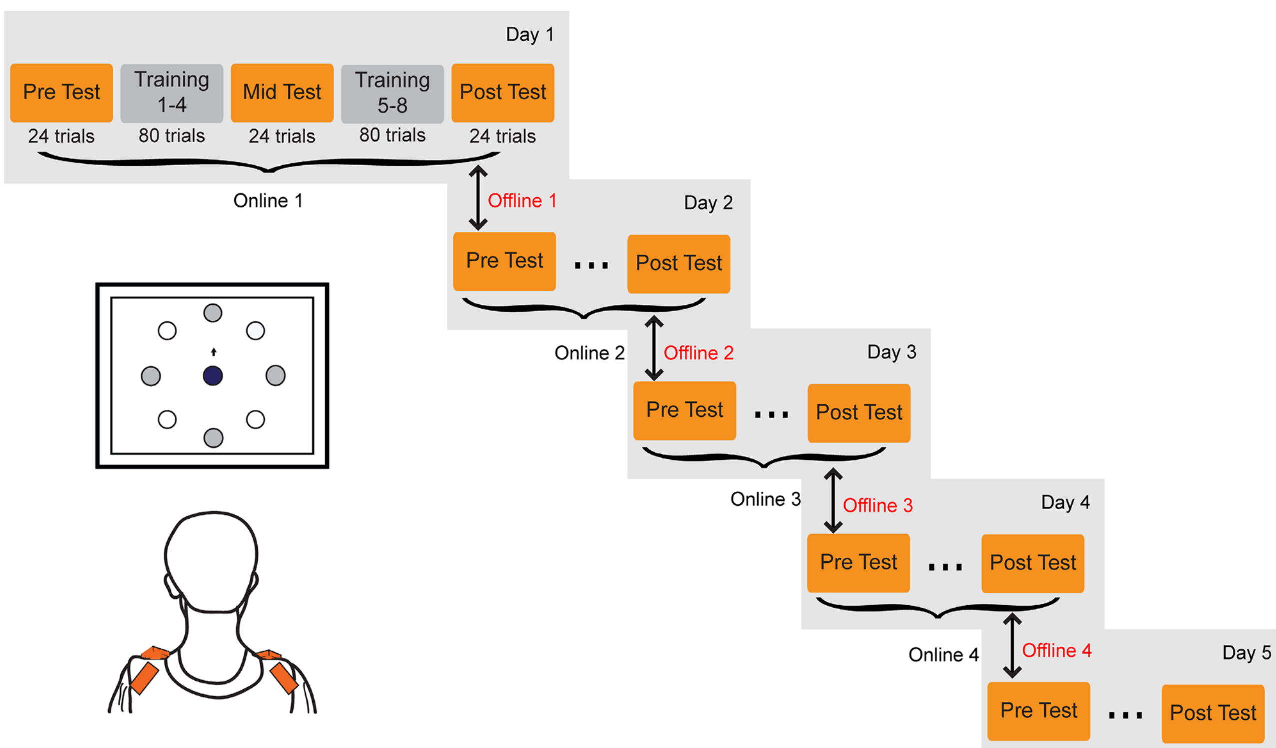

Fig. 1 Schematic of experimental setup and protocol. Participants from different age groups (8–10 years, 11–13 years, adults) learned to control a screen cursor and reach to different virtual targets using motions of the shoulder and torso. Participants practiced the task for 5 days and we examined learning using pre-test, mid-test and post-test blocks at the beginning, middle and end of each day, respectively. The '…' symbol indicates that the protocol in days 2–5 was identical to that on day 1. Training blocks included targets in the cardinal directions (shaded circles), whereas the test blocks included targets in both cardinal (shaded circles) and intercardinal directions (open circles). Online learning (indicated by curled parentheses) on any given day was quantified based on the relative difference in performance between the pre-test and post-test block. Offline learning (indicated by double-sided arrows) was quantified based on relative difference in performance between the post-test block on the previous day and the pre-test on that day

presented before a target could repeat. Each day consisted of 232 trials lasting typically 45–90 min. Participants performed this task for 5 days with an approximately 48-h gap between each session.

Data analysis

All analyses were performed only on the outward movements—i.e., when the participant moved from the home position toward the peripheral targets. Only data from the pre- and post-tests were included for analyses. The mid-test was used as part of the protocol—however, because the focus of the current study was on within- and between-day learning, the mid-test data were not used for analysis.

Movement time

Based on the fact that our protocol required participants to reach the target before the next target was presented (i.e., spatial error is ~0), and all targets were equidistant from the home position, we quantified task performance using the movement time. Movement time was calculated from the time that the cursor left the home position to the time that it reached and stayed inside the target for the subsequent 500 ms. The return movement from the target to the home position was not analyzed.

Normalized path length

The normalized path length was a secondary measure that was used to compute the straightness of the trajectories to the target. 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).

Online learning

The measure of 'online' learning was calculated based on changes in the movement time from pre- to post-test on each day, expressed as a percentage of the pre-test score. For example on day 1, online learning = $(MT_{\text{Pre-test1}} - MT_{\text{Post-test1}})/(MT_{\text{Pre-test1}}) \times 100$. We used a percentage change (rather than the raw difference in movement time) to account for baseline differences in performance between children and adults. Similar calculations were performed for the normalized path length.

Offline learning

The measure of 'offline' learning was calculated based on changes from post-test on a given day to the previous day to the pre-test on the subsequent day, expressed as a percentage of the post-test score. Again, we used a percentage change to account for any potential baseline differences in performance. For example on day 1, offline learning = $(MT_{\text{Post-test1}} - MT_{\text{Pre-test2}})/(MT_{\text{Post-test1}}) \times 100$. In this convention, a negative number for offline learning would indicate a 'warm-up decrement'—i.e., movement times were longer and task performance got worse after the period of no practice. Similar calculations were performed for the normalized path length.

Statistical analysis

For the purpose of this study, which focused on the contribution of online and offline components to overall learning, we focused on the four pre-tests that were done 'after' practice—i.e., pre-test from days 2 to 5. These four tests are critical to establish learning since they are essentially delayed retention tests. We then examined how the online and offline learning contributed to performance on each of these tests. For example, the pre-test on day 2 is determined by the online and offline component on day 1 (Fig. 1).

Movement time on the four pre-tests after initial practice (i.e., pre-test 2 to pre-test 5) was analyzed using a 4 × 3 (day × group) repeated measures ANOVA with day as the within-subject factor, and group as the between-subject factor.

The online and offline contribution for these four tests were analyzed using a 4 × 3 × 2 (day × group × type) repeated measures ANOVA, where type represents online vs. offline learning. There were only 4 days used in the analysis because our last test measure was the pre-test on day 5 (which meant that the online learning in day 5 was not used for analysis).

Violations of sphericity were corrected using the Greenhouse–Geisser factor when applicable. Significance levels were set at $p < 0.05$. Statistics were run using JASP (JASP Team 2018).

Results

Task performance

Movement time

There was a significant main effect of day [$F(1.73,46.85) = 9.771$, $p < 0.001$] and group [$F(2,27) = 6.719$, $p = 0.004$] (Fig. 2a). The day × group interaction was not significant [$F(3.47,46.85) = 0.785$, $p = 0.524$]. Post hoc comparisons showed that as expected, movement times decreased with practice, and that 8–10-year-old children had longer movement times compared to both

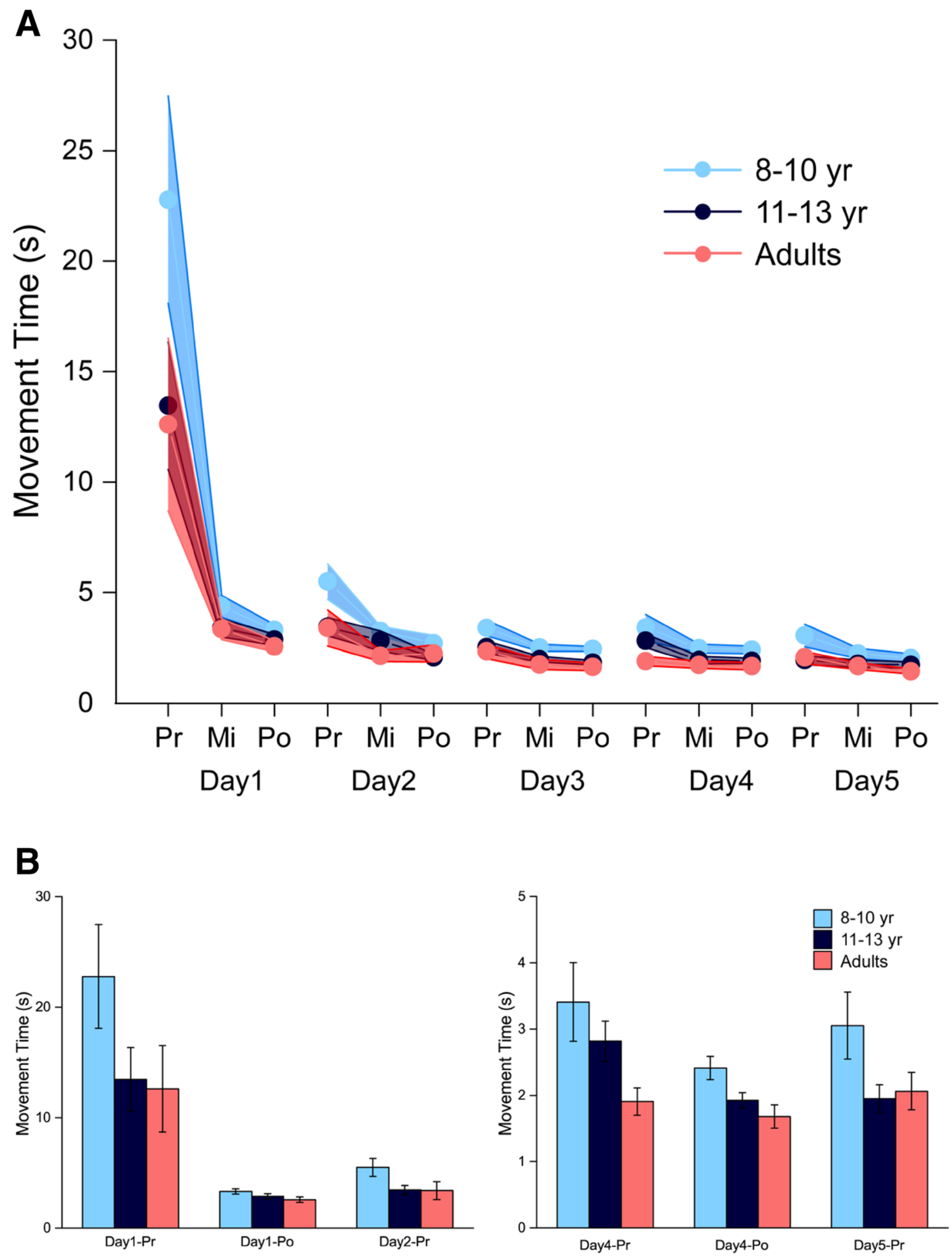

Fig. 2 **a** Movement time changes in all groups as a function of practice (*Pr* pre-test, *Mi* mid-test, *Po* post-test). All groups improved with practice but 8–10-year-old children showed longer movement times relative to both 11–13 year olds and adults. **b** Online and offline performance on days 1/2 and days 4/5 showing the first and last blocks of online and offline learning. When expressed as a percentage, both children and adults showed similar online performance gains and offline performance losses (i.e., warm-up decrement)

11–13 year olds ($p = 0.024$) and adults ($p = 0.005$) (Fig. 2b). There were no differences between 11–13 year olds and adults ($p = 0.802$).

Normalized path length

The normalized path length also showed similar results to movement time. There was a significant main effect of day [$F(1.70,45.81) = 5.842$, $p = 0.008$] and group [$F(2,27) = 5.850$, $p = 0.008$] (Fig. 3a). The day × group interaction was not significant [$F(3.39,45.81) = 0.881$, $p = 0.469$]. Post hoc comparisons showed that as expected, path length decreased with practice, and that 8–10-year-old children had longer path length compared to both 11–13 year olds ($p = 0.039$) and adults ($p = 0.011$) (Fig. 3b). There were no differences between 11–13 year olds and adults ($p > 0.999$).

Online and offline learning

Movement time

The ANOVA revealed a significant main effect of type [$F(1,27) = 83.378$, $p < 0.001$], day [$F(2.18,58.87) = 4.007$, $p = 0.02$] and a type × day interaction [$F(2.28,61.61) = 19.06$, $p < 0.001$]. The analysis of the type × day interaction showed that the contribution of online learning decreased

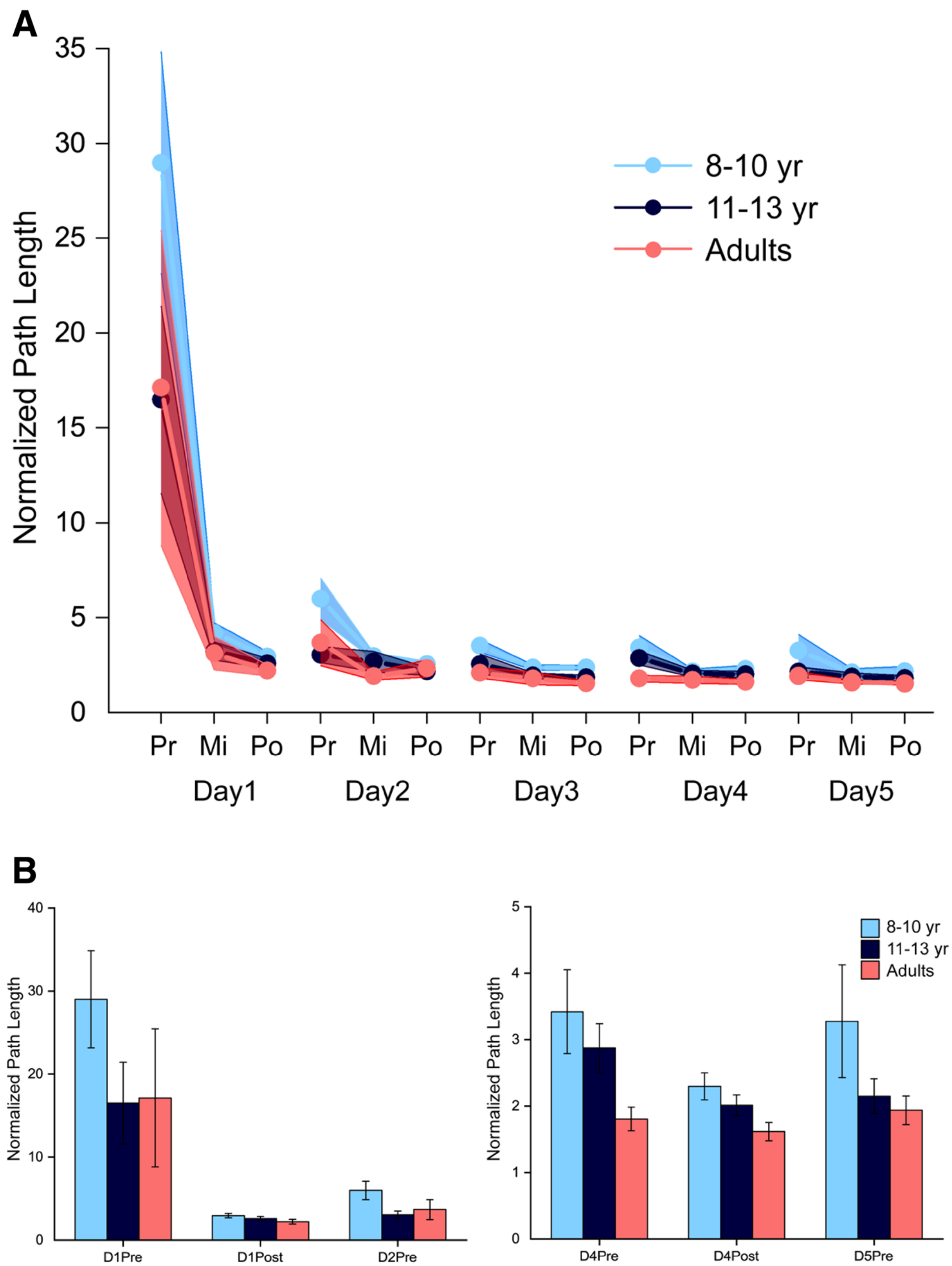

Fig. 3 **a** Normalized path length changes in all groups as a function of practice (*Pr* pre-test, *Mi* mid-test, *Po* post-test). All groups improved with practice but 8–10-year-old children showed longer normalized path lengths relative to both 11–13 year olds and adults. **b** Online and offline performance on days 1/2 and days 4/5 showing the first and last blocks of online and offline learning. When expressed as a percentage, both children and adults showed similar online performance gains and offline performance losses (i.e., warm-up decrement)

with practice, from day 1 to day 4 ($p < 0.001$) (Fig. 4a), but the contribution of offline learning remained unaffected ($p = 0.351$) (Fig. 4b). All other effects were not significant—main effect of group, [$F(2,27) = 0.372$, $p = 0.693$], type × group [$F(2,27) = 1.378$, $p = 0.269$], day × group [$F(4.36,58.87) = 0.801$, $p = 0.539$], and type × day × group [$F(4.56,61.61) = 1.144$, $p = 0.346$].

Normalized path length

The ANOVA revealed a significant main effect of type [$F(1,27) = 50.512$, $p < 0.001$], and a type × day interaction [$F(1.66,44.72) = 8.774$, $p = 0.001$]. The analysis of the type × day interaction showed that the contribution of online learning decreased with practice, from day 1 to day 4 ($p < 0.001$) (Fig. 4c), but the contribution of offline learning remained unaffected ($p = 0.099$) (Fig. 4d). All other effects were not significant—main effect of group, [$F(2,27) = 0.705$, $p = 0.503$], type × group [$F(2,27) = 2.317$, $p = 0.118$], day [$F(1.53,41.20) = 0.441$, $p = 0.593$] day × group [$F(3.05,41.12) = 0.768$, $p = 0.521$], and type × day × group [$F(3.31,44.72) = 0.806$, $p = 0.508$].

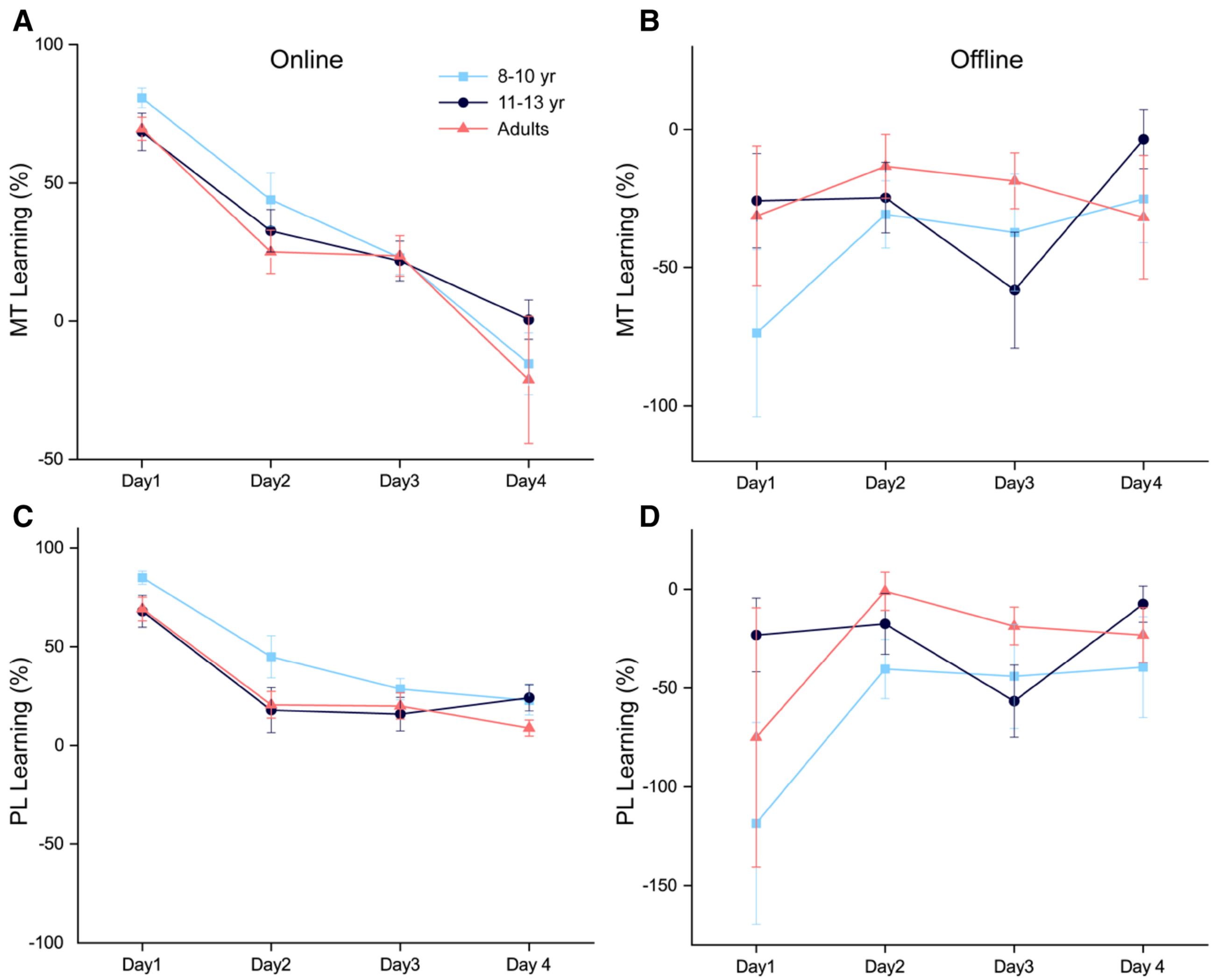

Fig. 4 Online and offline learning as a function of both practice and group based on the movement time (**a**, **b**) and the normalized path length (**c**, **d**). Negative numbers in offline learning indicate warm-up decrement. There were distinct changes with practice, with online learning showing a decrease with practice, whereas offline learning was relatively stable across practice. There were no statistically significant differences between groups in either online or offline learning

Discussion

In this study, we examined two primary research questions: (1) do children show deficits in motor learning of a novel task relative to adults even after relatively extensive practice, and (2) how are the contribution of the offline and online components of learning in this task affected by both age and practice? Our results showed that (1) even though all age groups improved with practice, there were persistent age-related differences in task performance even after 5 days of practice with the younger children (i.e., 8–10 year olds) showing longer movement times, (2) the amount of online and offline learning showed distinct changes with practice, but did not seem to be differentially influenced by age group.

First, we found that consistent with prior studies (Lee et al. 2018), younger children (8–10 year olds) showed longer movement times across all days of practice. In prior studies with shorter time intervals of learning, one potential confound was that because of the novel nature of the task, children might have showed poor performance because they just took longer to get used to the task. Here, we show that even after 5 days of learning (~ 1000 + trials), when performance has reached a relative asymptote, there were still reliable differences between the youngest children and adults, with 8–10 year olds being ~ 50% slower, corresponding to about 1 s overall. Although interpretations of 'learning' are difficult when there are differences in baseline (because conclusions may differ based on how learning is defined), our results support the notion that developmental differences in learning are not simply artifacts of novel experimental paradigms.

Second, when we parsed out the contribution of online vs. offline components to these learning differences, we found three key results—(1) online learning resulted in performance gains (i.e., reductions in movement time), whereas offline learning resulted in performance decrements (i.e., increases in movement time), and (2) the amount of online learning (measured as a relative %) decreased from days 1 to 4, whereas the amount of offline learning remained relatively constant throughout practice, and (3) these changes in online and offline learning were not affected by age.

These results are consistent with the view that the process of learning consists of multiple processes that operate at distinct timescales (Newell et al. 2001; Smith et al. 2006). While prior studies have either used a single snapshot of these processes, or averaged across multiple days (Reis et al. 2009), we focused on whether the amount of online and offline learning change with practice. While it is somewhat obvious that the 'absolute' change (i.e., change measured in seconds) would decrease with learning since there is less room to improve as participants reach a plateau, the decrease in the amount of online learning even when expressed as a 'relative' change (i.e., change measured in %) is less obvious and potentially suggestive of a power-law and the presence of multiple time scales (Newell et al. 2001). On the other hand, the amount of offline learning, which remained relatively fixed, was more characteristic of an exponential with one characteristic time scale (Joseph et al. 2013). Although these results are based on group averages, which are less interpretable than individual curve fits, they do suggest the possibility that the dynamics of the online and offline processes are distinct. The suggestion that these are two distinct processes also raises the possibility that they can be differentially affected by learning strategies (e.g., a strategy that improves within-session learning may not improve the between-session learning). Future experiments with extended periods of training are needed to resolve this issue in more detail.

When we examined the effect of age on the amount of online vs. offline learning, we did not find any evidence for any such influence. The result that age did not differentially affect online vs. offline learning is somewhat at odds with prior literature which has shown that such differences exist (Du et al. 2017; Yan 2017). As mentioned in the "Introduction", there are two main differences from prior work. First, the use of a task that shows warm-up decrement may be qualitatively different from sequence learning tasks that show offline gains. Although there are multiple theoretical perspectives on the issue of warm-up (Nacson and Schmidt 1971; Ajemian et al. 2010), there is no clear consensus on whether the difference between tasks showing warm-up decrement and consolidation are related directly to the task itself (Reis et al. 2009), or to methodological issues of how learning is analyzed (Pan and Rickard 2015). Relatedly, a second important difference from prior studies relates to methodological consideration of using 'absolute' change or 'relative' change in performances. This is because in the context of development, where groups are known to differ at baseline, absolute change scores might be skewed because groups who are worse at task performance have greater room for improvement. In our case, when we used a relative measure to compute the amount of online and offline learning, we found no reliable age effect, indicating that while children take longer to do the task, they do not proportionally take longer. It is also worth noting that the age groups used in prior studies vary based on the task used (around 5–7 years old); this variation may also contribute to some of the differences observed in the current study, which used relatively older children (8–13 year olds).

There are some limitations to the current work—first, the sample size in each group was relatively small, which was limited mainly by the relatively long practice period per participant. In addition, the age ranges within each of the children groups were somewhat wide, potentially causing some heterogeneity within the groups. Second, because we did a ~48-h rest period, we cannot disentangle if the offline effects were 'rest-related' and/or 'sleep-related' (Doyon et al. 2009). Third, we used average measures in each test block to quantify learning. It is possible that such averaging may create artifacts of offline learning (Pan and Rickard 2015) and may obscure the true timescale of change (Heathcote et al. 2000; Newell et al. 2001). However, given that our task involved reaching to eight different targets (instead of typical studies where the same task is repeated on every trial), we felt that an average measure over the entire set of reaches was likely a more robust measure of learning than the individual trial measures. Finally, although we used movement time as the primary measure based on the task instruction, children and adults could have had qualitatively different strategies in performing the task—for e.g., children could have had less reaction time and tried to correct for movements on the fly whereas adults may have longer reaction time to improve planning of the movements. We do not think this is likely because all measures showed the same trends with learning in both children and adults; however, this could be an issue investigated more conclusively in a future study.

In conclusion, we found that when learning a novel motor task, children show sustained worse performance compared to adults across multiple days of practice. The contribution of online and offline learning itself changed with practice, but did not seem to be affected by age. These results suggest that simply practicing for longer is unlikely to close the gap between children and adults, and point to the need for practice schedules to be customized in children.

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