Title

Neural correlates of motor sequence learning and enhanced offline consolidation in 7- to 11-year-old children

Authors

Anke Van Roy[1], Ainsley Temudo[1], Vincent Koppelmans[2,3], Kerstin Hödlmoser[4,5], Genevieve Albouy[1], Bradley R. King[1*]

Affiliations

[1] Department of Health and Kinesiology, College of Health, University of Utah, Salt Lake City, UT 84112, USA

[2] Department of Psychiatry, University of Utah, Salt Lake City, UT 84112, USA

[3] Huntsman Mental Health Institute, University of Utah, Salt Lake City, UT 84112, USA

[4] Department of Psychology, University of Salzburg, 5020 Salzburg, Austria

[5] Centre for Cognitive Neuroscience Salzburg, University of Salzburg, 5020 Salzburg, Austria

[*] **Corresponding author**

Bradley King, PhD

Department of Health & Kinesiology, College of Health, University of Utah

250 S 1850 E

Salt Lake City, Utah 84112

Bradley.ross.king@utah.edu

Abstract *(max. 200 words)*

Intro: Many daily activities involve series of interrelated movements and thus the capacity to learn new motor sequences is vital for everyday functioning. Although learning new skills is especially prominent throughout childhood, remarkably few studies have examined the neural underpinnings of motor sequence learning (MSL) and memory consolidation in children. **Methods:** Twenty-two children (7-11 years) and 23 adults (18-30 years) underwent functional magnetic resonance imaging while completing two sessions of a MSL task, separated by a 5-hour offline period of wakefulness. **Results:** Analyses of the behavioral data revealed comparable initial learning in children and adults. However, and consistent with previous research, children exhibited superior motor memory consolidation over the 5-hour offline epoch. Neuroimaging analyses revealed that children exhibited smaller modulations in brain activity between task and rest epochs in a widespread network, including the sensorimotor cortex, supplementary motor area, cerebellum, putamen and regions associated with the default mode network. Similar levels of activity during task and rest epochs in the hippocampus, dorsolateral prefrontal cortex and somatosensory cortex were associated with better motor memory consolidation in children. **Conclusion**: Results potentially suggest that the continued engagement of the developing brain during interleaved rest contributes to the childhood advantage in motor memory consolidation.

Keywords

development ● fMRI ● memory consolidation ● motor learning

1. Introduction

Many daily activities performed throughout the human lifespan rely on the successful execution of movement sequences (e.g., eating with utensils, tying shoelaces, typing a text message, etc.). Consequently, the capacity to acquire novel movement sequences is vital throughout one's life and thus an understanding of the underlying neural processes is critical. Prior research has extensively examined the behavioral and neural correlates of motor sequence learning (MSL) in healthy young adults (~18-35 years; see Albouy et al., 2013; Doyon et al., 2018; King et al., 2017; Krakauer et al., 2019 for reviews), an age group that is often considered the model of optimal functioning (e.g., Leversen et al., 2012). In brief, the initial learning of a motor sequence is characterized by rapid performance improvements and is supported by distinct neural networks that present different dynamical patterns of activity (Albouy, King, et al., 2013; Doyon, Bellec, et al., 2009; Hikosaka et al., 2002). An associative brain network that includes the hippocampus, associative territories of the striatum and cerebellum, as well as frontal and parietal areas is heavily recruited during early task practice and exhibits subsequent decreases as a function of learning. Conversely, activity in a sensorimotor network encompassing motor cortical areas, the sensorimotor striatum and cerebellum increases as learning progresses.

The "offline" (i.e., in the absence of active task practice) periods that follow initial learning afford the opportunity for the recently acquired memory trace to be consolidated into a stable, long-term form. Previous neuroimaging studies have revealed that changes in brain activity across an offline consolidation epoch often depend on whether this interval includes sleep. Specifically, activity in hippocampo-frontal and motor cortical areas increases following offline periods that include sleep (Albouy, King, et al., 2013; Debas et al., 2010; Walker et al., 2005), whereas awake consolidation

appears to be supported by increases in primary motor and parietal cortices (Albouy et al., 2008; Robertson et al., 2005; Wang et al., 2024). Changes in striatal activity are less dependent on vigilance state, as increases in activity have been observed across offline periods that include sleep as well as only wakefulness (Albouy et al., 2013). The research reviewed above characterized the neural correlates associated with the traditional "slow" consolidation process that takes place on the "macro-offline" timescale (i.e., hours to days following initial training). More recent work has suggested that consolidation also occurs on a faster "micro-offline" timescale (i.e., the seconds to minutes that constitute the brief rest periods between practice blocks; Bönstrup et al., 2019; Buch et al., 2021; Du et al., 2017; Gann et al., 2023; Jacobacci et al., 2020). Offline processing on the micro-timescale has been linked to activity in the hippocampus and caudate nucleus (Buch et al., 2021; Chen et al., 2024; Gann et al., 2023; Jacobacci et al., 2020; Sjøgård et al., 2024).

In contrast to the abundance of prior research that has examined the neural underpinnings of motor sequence learning in young adults, remarkably few studies have done so in children and these have largely been limited to the initial learning session [e.g., (Hedenius & Persson, 2022; Thomas et al., 2004)]. Results revealed age-group differences in the activation of motor-related brain regions during initial learning, with children and adults exhibiting greater recruitment of subcortical (e.g., putamen) and cortical areas (e.g., premotor cortex), respectively. The limited number of neuroimaging studies in pediatric samples is especially striking given that childhood is a time when learning new skills is very prominent and the developing brain exhibits heightened plasticity (see Ismail et al., 2017 for a review) that may provide children with a unique capacity for enhanced skill development. For example, whereas previous research has produced mixed results with respect to differences in initial learning between children and adults (Adi-Japha et al., 2014;

Fischer et al., 2007; Janacsek et al., 2012; Meulemans et al., 1998; Salehi et al., 2016; Wilhelm et al., 2008) research from our team and others have provided behavioral evidence suggesting that children (~7-12 years) exhibit superior macro-offline consolidation following a period of post-learning wakefulness as compared to adults (Adi-Japha et al., 2014; Ashtamker & Karni, 2013; Dorfberger et al., 2007; Van Roy et al., 2024). There is also evidence to suggest that such a childhood advantage may not be limited to the macro-offline timescale. Young children (i.e., 6 year-olds) also showed greater performance gains across the micro-offline rest periods interspersed with blocks of active task practice during an initial learning session (Du et al., 2017). The neural correlates of these behavioral advantages in offline processing remain unknown.

The aim of the current research was to examine the neural substrates supporting motor sequence learning as well as the developmental advantage in awake offline consolidation processes in children. To do so, 7- to 11-year-old children and 18–to 30-year-old adults performed a MSL task during two learning sessions, separated by a 5-hour offline period of wakefulness. Using magnetic resonance imaging (MRI), functional brain images were acquired during both sessions, affording the assessment of age group differences in task-related brain activation during learning as well as changes in activity across the 5-hour macro-offline period. Similar to our previous behavioral study (Van Roy et al., 2024), we hypothesized that learning dynamics (i.e., block-to-block performance changes) during initial learning would be comparable in the two age groups; however, children were predicted to have smaller micro-online and larger micro-offline gains as compared to adults. During this initial acquisition phase, and in line with Thomas et al. (2004), children were expected to exhibit greater task-related activation of the striatum and hippocampus, whereas adults would show greater cortical brain activity. We predicted that these differences in task-related brain

activity would be associated with the behavioral micro-online and -offline performance gains. Following initial learning, we hypothesized that – in line with our prior study (Van Roy et al., 2024) – children would exhibit a behavioral advantage in performance gains across the 5-hour offline period. At the neural level, we expected that both children and adults would show increases in activity in the hippocampus and striato-motor regions across the consolidation interval, with larger increases in children. These activity changes were anticipated to be related to the greater macro-offline performance changes in children.

2. Methods and materials

Data collection and analysis plans were registered in April 2024 via Open Science Framework and can be accessed at https://doi.org/10.17605/OSF.IO/SW6D8. Any deviations from the registered procedures are marked in this text with an asterisk and additional details for the deviations are provided in Appendix 1 as part of the Supplementary Material. Any analytic procedures that were not included in the registration are labeled as exploratory in this text. Note that prior to the registration, 27 (out of 45 included) datasets were acquired and 18 were processed using preliminary analytic scripts. These analyses served to assess data quality (i.e., keypresses and their timing were logged adequately, acquired images were of sufficient quality, and that saved and exported data were complete) and were also used as pilot data for funding applications. The data that support the findings of this study are openly available on Zenodo at https://doi.org/10.5281/zenodo.16891677. The study protocol was approved by the University of Utah Ethics Committee (IRB_00155118) and experimental procedures were conducted according to the declaration of Helsinki (2013).

133 *2.1 Participants*

134 A convenience sample of seemingly healthy children (operationally defined as 6-12 years) and
135 adults (18-30 years) of all genders was recruited via advertisements posted in public spaces and
136 on relevant websites. Eligibility was assessed based on self- or parental report via an online
137 screening questionnaire. Exclusion criteria were: 1) left-handed; 2) history of medical,
138 neurological, psychological, or psychiatric conditions, including depression and anxiety; 3)
139 consumption of psychotropic or psychoactive medications; 4) self-reported indications of
140 abnormal or irregular sleep; 5) mobility limitations of the fingers/hands that could prevent
141 successful motor task completion; 6) extensive training in a musical instrument requiring
142 dexterous finger movements (e.g., piano, guitar) or as a typist; 7) previous participation in a
143 research experiment employing a similar motor sequence learning task; and, 8) presence of MRI
144 contraindications (including claustrophobia). Adult participants and parents of child participants
145 gave informed consent, and children 7 to 12 years of age gave informed assent (i.e., children of 6
146 years were not required to provide assent). Note that although 6- to 12-year-old children were
147 recruited, our final sample of child participants was limited to 7-11-year-olds (see Appendix 1 for
148 information on attrition).

149

150 Sample size estimation was conducted *a priori* and with the software G*Power (Faul et al., 2007).
151 The effect size of interest was set to d = 0.76 and computed as the average effect size from the
152 behavioral results of two published studies assessing motor memory consolidation over post-
153 learning wake intervals in children and adults. Specifically, the comparison in 5hr offline
154 performance changes between children and young adults in Van Roy et al., (2024) corresponded
155 to Cohen's d = 0.6. In Ashtamker and Karni (2013), Cohen's d was estimated to be 0.92 based on

the data depicted. To detect a childhood advantage in motor memory consolidation across a period of wakefulness using a one-tailed independent samples t-test with an effect size of d = 0.76, α = 0.05 and a desired power of 0.80, the desired sample size was 46 participants (23 children; 23 adults). A total of 61 participants (36 children, 25 adults) enrolled in the study. Sixteen of these participants (14 children) did not complete the experiment (see flow diagram for inclusion and exclusion in Appendix 1). Due to a rate of exclusion that was slightly higher than expected for children, our final sample included 22 children and 23 adults and thus was one child short of the registered sample size. Note that a subset of participants was excluded from specific analyses due to excessive head motion or deviations from the experimental protocol (see Appendix 1 for details). All figure and table captions in the main text and Supplementary Tables explicitly state the sample size included in the corresponding analysis.

Potential age group differences in participant characteristics, sleep, vigilance and protocol timing were assessed using independent samples t-test or Mann-Whitney U tests, depending on whether the data were normally distributed. These measures included morningness/eveningness (self-report), self-reported sleep quantity and quality of the night prior to the experimental day, time of testing of each session and the duration of the offline period between initial training and the 5-hour delayed retest. Furthermore, objective and subjective measures of vigilance at the time of testing (see Section 2.2) were compared between age groups and sessions using a group (2 levels: children vs. adults) by session (2 levels: training vs. retest session) mixed ANOVA.

176 *2.2 Experimental procedure*

177 Participation in this research consisted of an initial familiarization visit followed by two
178 experimental sessions that took place on the same day (see Figure 1). Participants were asked to
179 have a good night of sleep the night prior to each testing day. The first visit consisted of a short
180 familiarization session (~1 hour) that was scheduled based on participant availability but restricted
181 to between 9 am and 6 pm. The purpose of this session was to familiarize participants to the
182 research team, MRI environment and motor tasks. A detailed description of the familiarization
183 procedure is provided in Appendix 1. At the end of the familiarization session, participants were
184 given a sleep diary on which they were asked to record their sleep times starting three nights prior
185 to the experimental visit. Ideally, the experimental session occurred at least two days following
186 the familiarization session, but this was not always possible given the schedules of two
187 participants. The duration between these two visits ranged from 0 (one adult) to 29 days (medians
188 for children and adults were 6.5 and 4 days, respectively).

189

190 The primary experimental day consisted of two sessions, herein referred to as training and retest,
191 completed approximately 5 hours apart (see Table 1 for details on the duration of this between-
192 session interval). The training session took place in the morning between 9 am and 1:30 pm. The
193 5-hour delayed retest session was thus scheduled between 2 pm and 6:30 pm, affording the
194 assessment of motor memory consolidation after an interval of post-learning wakefulness.

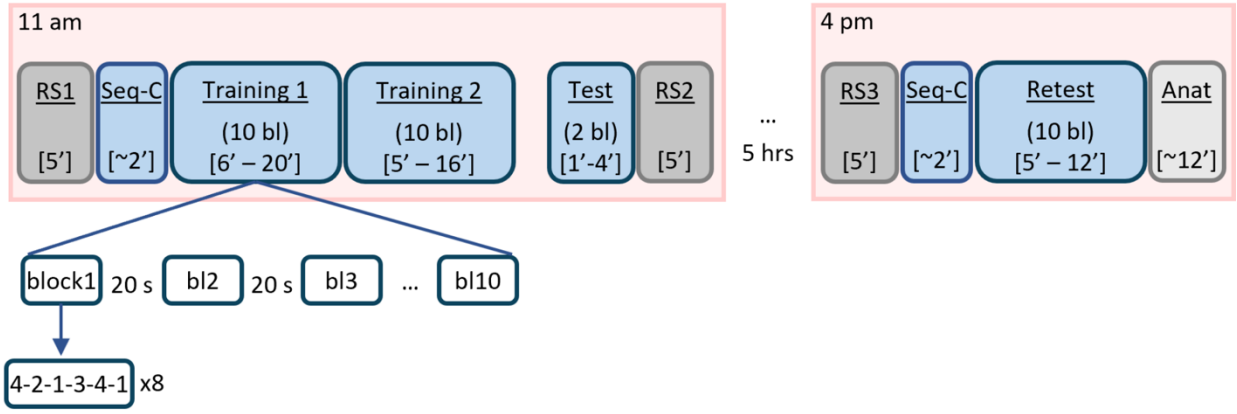

Figure 1. Design for the experimental sessions. Initial training on the finger tapping task (FTT) was divided into training 1, training 2 and test runs. The test run provided a behavioral measure of end-of-training performance after the dissipation of fatigue (Pan & Rickard, 2015). Resting-state (RS) scans were acquired prior to and following the FTT task runs (RS data not included in this manuscript). Following a 5-hour macro-offline consolidation interval, participants completed another RS scan followed by a retest of the motor task. In all FTT runs, blocks of task practice were alternated with 20s rest epochs, affording the assessment of micro-online and -offline learning. hrs = hours. Seq-C = sequence-check. Anat = anatomical T1- and T2-weighted images. Anatomical data were originally acquired at the end of the retest session (i.e., for the first 10 children and 15 adults). However, to check that participants were comfortable with the real scanning environment prior to the experimental visit, the acquisition of the structural images was moved to the end of the familiarization session for the last 12 children and 8 adults included in the analyses. Durations of runs are indicated between brackets. Note that ranges were provided for task runs since durations depended on individual performance. Pink shaded regions depict instances when participants were in the MRI scanner. BOLD images were acquired during RS and FTT task runs, except for the sequence-check runs.

At the beginning of the training session, participants returned their completed sleep diary and re-verified that they did not present any MRI contra-indications. This was followed by answering brief questionnaires reporting on their sleep patterns in the previous 24 hours, their subjective feelings of alertness (Stanford Sleepiness Scale; Maclean et al. 1992), intake of medicine in the past 3 days, as well as any exercise and consumption of alcohol and/or recreational drugs in the last 24 hours (alcohol and drug intake for adult participants only). Subjects also completed a modified version of the Psychomotor Vigilance Task (PVT; Dinges & Powell, 1985) to obtain an objective assessment of vigilance/alertness at the time of testing. Briefly, participants were asked

222 to fixate on the middle of the computer screen. Following varying delay intervals, a visual stimulus
223 appeared, and participants were instructed to respond by pressing the space bar as fast as possible.
224 A shortened version of the PVT was administered (validated in Basner et al., 2011 and Loh et al.,
225 2004), consisting of 35 trials, the first 5 of which were considered practice trials and excluded
226 from analyses. The response times (i.e., time between appearance of stimulus and the keypress;
227 RT) were logged and used to assess vigilance (i.e., higher RTs indicate lower vigilance). Following
228 the PVT, participants completed 5 blocks of the pseudorandom SRTT in the mock scanner to assess
229 general motor execution without engaging sequence learning processes, as well as the FTT
230 habituation procedures at a table outside the mock scanner. These tasks were administered to
231 ensure participants were comfortable with completing the motor tasks and the simulated MR
232 environment prior to entering the real MR environment and initiating the portion of the protocol
233 used for data analyses. Accordingly, data from the SRTT and familiarization procedure were not
234 analyzed.
235
236 Participants were subsequently positioned in the 3-Tesla MR scanner with an MR compatible
237 keyboard on each hand. Following a pre-training resting-state run (RS1), participants were
238 introduced to the experimental sequence (4-2-1-3-4-1, where 1 is the left middle finger, 2 is the
239 left index finger, 3 is the right index finger and 4 is the right middle finger) during a short sequence-
240 check. Specifically, participants were provided with this sequence of keypresses for the first time
241 and were asked to perform the sequence slowly and as accurately as possible. This sequence-check
242 ended when 3 correct sequences were performed consecutively and ensured that participants could
243 perform the sequence prior to starting the training runs. Participants then completed the initial
244 learning session of the FTT task (see section 2.3) while blood-oxygen-level-dependent (BOLD)

245 images were acquired (see Section 2.5). This session was organized into 3 runs, two training runs
246 of 10 blocks followed by a test phase of 2 blocks. We elected to decompose the training portion
247 into 2 runs to provide participants, particularly young children, with the opportunity to have a brief
248 rest and to communicate with the research team. The test run was administered approximately 1
249 minute after the second training run, affording the assessment of end-of-training performance
250 following the dissipation of mental and physical fatigue (Pan & Rickard, 2015). The initial learning
251 session concluded with a post-learning resting-state run (RS2). Participants were then permitted to
252 leave the imaging facility and were instructed to avoid strenuous exercise as well as caffeine (i.e.,
253 coffee, tea, energy drinks, soda). Importantly, as our research question is focused on offline
254 consolidation over wake intervals, participants were instructed to not sleep. Based on self-report,
255 no participants slept during the offline consolidation period.
256
257 Participants returned to the imaging center approximately 5 hours after the end of the training
258 session to complete the retest. Following vigilance assessments (i.e., PVT and SSS), participants
259 were positioned back in the MR scanner. This retest session included a pre-retest RS run (RS3)
260 and the sequence-check, followed by 10 blocks of the FTT.
261
262 Note that functional brain images were acquired during all FTT and RS runs, except for the
263 sequence-check. Analyses of RS data are not included in this manuscript. Images acquired during
264 the test run were not analyzed given the limited number of volumes. Anatomical data, consisting
265 of T1- and T2-weighted images, was originally acquired at the end of the retest session (i.e., for
266 the first 10 children and 15 adults). However, to check that participants were comfortable with the
267 real scanning environment prior to the experimental visit, the acquisition of the structural images

268 was moved to the end of the familiarization session for the last 12 children and 8 adults included
269 in the analyses. Participants were allowed to watch a movie or listen to music during the structural
270 scans.

271 *2.3 Finger Tapping Task (FTT)*

272 An explicit, bimanual finger tapping task (FTT) was employed, coded and implemented in the
273 MATLAB Psychophysics Toolbox version 3 (Kleiner et al., 2006). The task was analogous to our
274 earlier research (Dolfen et al., 2019), but was modified slightly for children (see Figure S2).
275 Specifically, participants used the index and middle fingers of both hands to press four keys on
276 specialized MR-compatible keypads (Celeritas fMRI Button Response System; Psychology
277 Software Tools, Pittsburgh, PA, USA). The task consisted of alternating practice and 20-second
278 rest blocks, indicated by green and red text, respectively. During each practice block, a green cross
279 and a 6-element sequence of numbers corresponding to the fingers to press (i.e., 4-2-1-3-4-1) were
280 displayed on the screen. Participants were asked to repeatedly tap the finger sequence on the
281 keyboard as rapidly and accurately as possible. Each practice block consisted of 48 keypresses
282 (i.e., ideally corresponding to 8 repetitions of the 6-element sequence) and ended once this number
283 of keypresses was recorded. During the rest periods, the cross turned red, and the sequence of
284 numbers was replaced by a fixed sequence of random symbols (i.e., @-!-$-%-&-#) displayed in
285 red to avoid exposure to the sequence during rest. Participants were asked to focus on the red cross
286 and to not move their fingers during these rest epochs. During performance of the FTT, the timing
287 and number of each keypress were recorded.

288 *2.4 Behavioral data analyses*

289 For each practice block of the FTT, performance speed was computed as the median time to
290 perform a transition between pairs of consecutive keypresses, and performance accuracy was
291 computed as the percentage of correct transitions. A transition was classified as "correct" if two
292 subsequent keys were pressed in the same order as presented in the sequence. Similar to our
293 previous research (Van Roy et al., 2024) and to account for expected age group differences in
294 movement speed and accuracy independent of sequence learning (i.e., baseline differences;
295 Meulemans et al. 1998; Sugawara et al. 2014; Salehi et al. 2016), outcome variables from task runs
296 were normalized relative to outcome variables from the first training block. Specifically, for each
297 outcome measure and each block of the FTT runs, performance was divided by the median
298 outcome measure of the first block of training 1. Per our registration, statistical analyses on these
299 normalized measures are presented in the main text. For completeness, results based on exploratory
300 analyses on the non-normalized outcome measures (i.e., transition time and % of correct
301 transitions) and the variables computed using these measures (i.e., micro-online and -offline
302 performance changes, macro-offline performance changes) are reported in Appendix 3.

303

304 All behavioral statistical testing described below was performed using R version 4.5.1 (Posit, PBC,
305 Boston, Massachusetts, USA). Statistical tests were considered significant when $p < 0.05$.
306 However, for completeness, we also highlight those effects when $0.05 < p < 0.1$ as non-significant
307 trends. For all mixed ANOVAs detailed below, Greenhouse-Geisser corrections were applied in
308 the event of a violation of sphericity. Effect size measures include eta-squared, partial eta-squared
309 or Hedge's g, depending on the statistical test. Null hypothesis testing for all behavioral effects
310 presented in the main text was supplemented by the computation of Bayes Factors (BF;

BayesFactor R-package; see Appendix 1 for details), reflecting the likelihood of the observed data favoring an alternative model (e.g., evidence for differences among groups, blocks, etc.) relative to the null model (i.e., no differences).

To assess potential age group differences in initial encoding of the motor sequence (i.e., prior to the macro-offline period), learning dynamics (i.e., block-to-block changes) were compared between groups using separate mixed ANOVAs for performance speed and accuracy with *group* (i.e., children vs. adults) as between-subject factor, and *run* (i.e., training 1 vs. training 2) and *block* (i.e., 10 training blocks) as within-subject factors. Similarly, to assess age group differences in continued performance of the motor sequence following the 5h offline interval, performance dynamics during retest were compared between groups using separate mixed ANOVAs with *group* (i.e., children vs. adults) as the between-subject and *block* (10 retest blocks) as the within-subject factor.

To examine the consolidation process on a macro-timescale, an "offline gain" measure was computed for each outcome variable. Specifically, the difference in normalized performance from the end of training (average across the 2 post-learning test blocks) to the beginning of the retest (average across the first 2 blocks) was calculated. The resulting measure reflects the offline change in performance from the end of the initial training session to the retest session and thus, is used as a measure of memory consolidation across the post-learning period of wakefulness. Per our registration, one-tailed independent samples t-tests were used to assess age group differences in the offline gain measures.

To obtain an assessment of performance that captures both performance components (i.e., speed and accuracy) in a single measure, a general performance index (GPI) was computed as an exploratory outcome metric. GPI was computed at the block level, using equation 2.1 below (similar to Reverberi et al. 2023). Subsequently, offline gains were calculated for the GPI, as the difference in GPI from the end of training (average across the 2 post-learning test blocks) to the beginning of the retest (average across the first 2 blocks). The GPI across practice blocks as well as macro-offline changes in GPI are depicted in Appendix 3.

$$\mathrm{GPI} = \exp(-(\text{med transition time}) * \exp\left(-\frac{100-\%\text{correct transitions}}{100}\right) * 100 \qquad \text{equation 2.1}$$

To assess performance changes on a micro-timescale, we distinguished between micro-online (i.e., within blocks of task practice) and micro-offline (i.e., between blocks of practice) performance improvements. As in our previous work (Van Roy et al., 2024), micro-*online* improvements were computed as the difference between the median normalized transition times of the first and last 6 transitions *within* each block. Micro-*offline* performance changes were computed as the difference between the median normalized transition times of the last 6 transitions of one block and the first 6 transitions of the subsequent block. The computations used six transitions to correspond to the five transitions between the six keypresses within a sequence, plus the transition between two consecutive sequences. To obtain a single micro-online and micro-offline value per training run, the micro-measures were averaged across task blocks or rest intervals, respectively, *within* training 1 and training 2 separately. Micro-online and -offline performance changes were subjected to separate 2 x 2 mixed ANOVAs with *group* (i.e., children vs. adults) as between-subject and training run (i.e., training 1 vs. training 2) as within-subject factor.

Registered analyses compared differences between age groups. Yet, to provide more fine-grained analyses of the development of motor memory consolidation behaviors, we also conducted exploratory analyses assessing age-related changes within our sample of child participants. Specifically, micro- and macro-offline performance changes were subjected to separate multiple regression analyses with age as a continuous independent variable. For both dependent measures, and consistent with our previous work (Van Roy et al., 2024), five potential fit options (i.e., single exponential, double exponential, linear, quadratic and power functions) were tested and the model with the lowest Akaike Information Criterion values was deemed as the best fitting model. Results from these regression analyses are provided in Appendix 3.

2.5 MRI data acquisition

MRI data were acquired on a Siemens MAGNETOM Vida 3.0T MRI system equipped with a 64-channel head coil. To minimize head motion, additional padding was placed around the head. For each participant, a high-resolution, T1-weighted structural image was acquired with a 3D MPRAGE sequence (axial; repetition time (TR) = 2500 ms; echo time (TE) = 2.98 ms; inversion time (TI) = 1070 ms; flip angle (FA) = 8°; 176 slices; field-of-view (FoV) = 256 x 256 x 176mm^3; voxel size = 1.0 x 1.0 x 1.0 mm^3; duration = 5:59 min). Parallel acquisition was conducted in the GRAPPA mode, with reference line phase encoding (PE = 32), and acceleration factors PE and 3D equal to 2 and 1, respectively. Analyses of the structural T2-weighted image are not included in this manuscript.

Resting-state (RS) and task-related fMRI data were acquired with an interleaved gradient EPI pulse sequence for T2*weighted images (SMS acceleration with multiband factor 5; TR = 797.0 ms; TE = 31.0 ms; flip angle = 59°; 55 transverse slices; voxel size = 2.5 x 2.5 x 2.5 mm^3; field of view = 220 x 220 x 138 mm^3). The task-related runs were set to a maximum of 1500 volumes, with a maximum duration of 20:03 minutes (including unsaved dummy pulses). These runs were terminated when participants completed all FTT practice blocks and thus the exact number of scans in each task run depended on each individual's performance speed (median number of scans for children: 1096 for training 1, 803 for training 2, 690 for retest; adults: 588 for training 1, 508 for training 2, 486 for retest).

Gradient-recalled echo (GRE) fieldmaps were acquired prior to task performance during the training and retest sessions to correct for distortions due to magnetic field inhomogeneities. Specifically, two phase-encoded GRE images with different echo times (TR = 752 ms; TE_1 = 5.19 ms, TE_2 = 7.65 ms; flip angle = 90°; 55 transverse slices; voxel size = 2.5 × 2.5 × 2.5 mm^3; field of view = 220 × 220 × 138 mm^3) were collected. Phase-difference maps were calculated from the two GRE images using in-scanner processing.

2.6 fMRI data analysis

Prior to any processing, the DICOM images output by the SIEMENS scanner were converted to BIDS using the dcm2bids tool (Boré et al., 2023), implemented in Python 3.11.5. Additionally, the T1-weighted images were reoriented to the Montreal Neurological Institute (MNI) template to facilitate spatial normalization. The section below details the initial spatial preprocessing that was performed in fMRIPrep 24.1.0* (Esteban et al., 2019). This is followed by a description of the

additional preprocessing and analyses performed in SPM12 (Wellcome Department of Imaging Neuroscience, London, UK) in Matlab R2023a.

2.6.1 Spatial preprocessing in fMRIPrep

Initial spatial preprocessing was performed in fMRIPrep 24.1.0 (Esteban et al., 2019). Appendix 1 contains a detailed description of the spatial preprocessing, which was automatically generated by fMRIPrep and released under the CC0 license. Here, we provide a brief description of the preprocessing steps that are relevant for analyses presented in this manuscript. The T1-weighted (T1w) anatomical scan underwent correction for intensity inhomogeneities, followed by skull-stripping and tissue segmentation into gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). For each functional task run, head motion parameters were estimated (i.e., translation and rotation in the three motion planes; see Appendix 4 for information on the magnitude of head motion). Functional images were then distortion-corrected using the GRE fieldmaps and subsequently co-registered to the T1w image.

To reduce the detrimental effect of excessive head motion, images or entire runs where head motion exceeded the pre-defined threshold of 5mm (~2 voxels) were removed. Details on head movement and data exclusion at the participant level are provided in Appendices 4 and 1, respectively. In brief, fMRI data from the training runs of 3 participants were truncated due to maximum head translation across any motion plane exceeding 5 mm. In the case of one child subject, head motion was large and consistent enough such that fMRI data from the entire Training 1 and Training 2 runs were excluded from analyses.

423 2.6.2 Univariate fMRI analysis

424 Additional preprocessing of the MRI images and statistical testing were performed in SPM12
425 (Wellcome Department of Imaging Neuroscience, London, UK). A sample-based DARTEL
426 (Diffeomorphic Anatomical Registration Through Exponentiated Lie algebra) template was built
427 independently of the spatial preprocessing in fMRIPrep. Specifically, the reoriented T1-weighted
428 image of each participant was segmented into 6 tissue types (i.e., white matter, gray matter,
429 cerebrospinal fluid, bone, soft tissue, background) and an average sample-based template was
430 created and registered to the MNI space using DARTEL (n = 45, 22 children, 23 adults). Each
431 subject's fMRIPrep-processed T1w image and functional images were then normalized to this
432 template. Additionally, functional images were spatially smoothed using an isotropic 8mm full-
433 width at half-maximum (FWHM) Gaussian kernel.

434

435 Activation analyses of task-based fMRI data were performed to assess age group differences in
436 the activation of task-relevant regions during initial learning as well as changes in activity across
437 the macro-offline consolidation interval. These analyses were conducted in two serial steps,
438 accounting for intraindividual (fixed effects) and interindividual (random effects) variance. At the
439 individual level, a general linear model (GLM) was built, estimating changes in regional brain
440 signals in response to practice of the FTT and its linear modulation by performance speed (i.e.,
441 median transition time per block). The 20-second rest blocks interspersed between blocks of FTT
442 practice served as the baseline condition, modeled implicitly in the block design. The regressor of
443 interest (i.e., task practice) consists of box cars convolved with the canonical hemodynamic
444 response function. Head motion estimates (i.e., translation and rotation in the three motion planes;
445 see Appendix 4 for head motion values per group) output by spatial pre-processing and erroneous

keypresses were included in the model as regressors of no interest in order to maximize the explained variance, and high-pass filtering with a cutoff period of 128s was implemented to remove slow drifts from the time series. Serial correlations in the fMRI signal were estimated using an autoregressive plus white noise model and a restricted maximum likelihood (ReML) algorithm.

Linear contrasts were generated at the individual level to test for (1) the effect of task practice (i.e., task-related activity) within each task run (i.e., training 1, training 2 and retest); (2) the linear modulation of task-related activity by performance speed within each task run (data not presented here); and, (3) the change of task-related activity between pairs of runs. For all linear contrasts, the resulting contrast images were further spatially smoothed using an isotropic 6mm FWHM Gaussian kernel and entered into a second-level analysis for statistical interference at the group level (i.e., independent samples t-test comparing children and adults). Such a group-level analysis corresponds to a random effects model that accounts for inter-subject variance. The set of voxel values resulting from each second-level analysis constitutes maps of the t-statistics [SPM(T)], thresholded at $p < 0.001$* (uncorrected for multiple comparisons). Significant brain clusters were visually inspected and were excluded when deemed to be fully located in white matter.

For results presented in the main text, statistical inferences were performed at a threshold of $p < 0.05$ after family-wise error (FWE) correction for multiple comparisons over small spherical volumes (small volume correction (SVC) approach; Poldrack, 2007; Poldrack et al., 2008). Specifically, for clusters within a priori-defined regions of interest (i.e., frontal, motor and parietal cortices, basal ganglia, thalamus, cerebellum and hippocampus, based on the AAL3 atlas of Rolls et al. 2020) that were significant at p(uncorrected)<0.001, coordinates in close proximity to the

activation peak were extracted from published motor sequence learning and memory consolidation research (see Appendix 1). Spheres (10 mm radius) were centered on these coordinates and correction for multiple comparisons was applied across voxels included in each spherical volume. Note that activations in occipital and temporal regions were ignored, as these regions are thought to not play a significant role in motor sequence learning and memory consolidation processes. All results reported and discussed in the main text survived SVC. An additional correction for multiple volumes of interest within each contrast was performed using Holm-Bonferroni procedures ($p < 0.05$; Holm, 1979). Results that survived this additional Holm-Bonferroni correction are simply indicated with an asterisk in the corresponding table.

To assess the link between brain activation and behavioral performance, the individual's contrast images from the activation-based analyses outlined above were regressed against the individual's behavioral performance measures. Specifically, we assessed the relationship between (1) task-related brain activity during training 1 and the respective micro-online and -offline performance changes; (2) task-related brain activity during training 2 and the respective micro-online and -offline performance changes; (3) task-related brain activity during training 1 and the macro-offline performance changes; (4) changes in brain activity from training 2 to the retest session (i.e., across the 5-hour offline period) and the macro-offline performance changes. Additionally, an exploratory analysis was conducted with the average (non-normalized) transition time in training 1 as a covariate of no interest. This allowed the determination of whether age group differences in task-related brain activity during training 1 remained after accounting for differences in performance speed. Results are provided in Appendix 5.

The analyses outlined above compared differences between the two age *groups*. To provide more fine-grained analyses of the development of task-induced activity, we also performed exploratory analyses assessing age-related changes in task-induced activity and changes in brain activity from initial training to the retest across childhood. Specifically, the previously described univariate fMRI analyses were run with age as a covariate in a regression analysis. Results of these analyses can be found in Appendix 5.

3. Results

3.1 Participant characteristics, sleep and vigilance

Table 1 provides group means of participant characteristics, self-reported sleep quality and duration for the night preceding the experimental day, subjective (SSS) and objective (PVT) measures of vigilance at time of FTT completion, as well as details on the timing of the experimental protocol. Results from the corresponding statistical analyses can be found in Appendix 2. In brief, significant age group differences were observed for sleep duration and performance on the psychomotor vigilance task (PVT). Specifically, children reported a longer sleep duration than adults for the night prior to the training session, reflecting the known decrease in total sleep time with age (Ohayon et al., 2004). Additionally, children performed slower on the PVT as compared to adults, which is in line with prior research (Iida et al., 2010). The main effect of session and the group by session interaction on the PVT data were not significant. This demonstrates that vigilance remained similar across the two sessions for the two groups and suggests that any observed behavioral and imaging results reported below cannot be attributed to changes in vigilance across the testing day.

513 **Table 1.** Participant demographics and sleep and vigilance scores for each age group

Variable		Children	Adults	p-value
n		22	23	
Female/Male/Non-Binary *(n)*		14/7/1	16/6/1	
Age (years)		9.5 (1.3)	23.4 (3.3)	
Race/Ethnicity	*Asian*	1	2	
	Black/African American	0	1	
	White	18	17	
	Mixed Race	2	2	
	Hispanic / Latino	1	1	
M/E preference		2.8 (0.7)	2.7 (0.9)	0.582
Training session	*Time of testing*	10:49 (49)	10:53 (62)	0.598
	Sleep quality	5.2 (0.7)	4.9 (0.8)	0.173
	Sleep duration (hrs.)	9.83 (0.83)	8.3 (0.9)	< 0.001*
	SSS score	2.3 (0.8)	2.0 (0.7)	0.346
	PVT score (ms)	393.7 (66.1)	298.0 (24.6)	< 0.001 *
Retest session	*Time of testing*	16:28 (45)	16:19 (59)	0.295
	Offline period (hrs.)	5.1 (0.7)	5.1 (0.4)	0.574
	SSS score	2.3 (0.8)	2.4 (1.1)	0.836
	PVT score (ms)	393.0 (54.9)	301.6 (29.7)	< 0.001*

514 Values for n, gender and race/ethnicity represent number of participants. For other values, the
515 numbers represent the mean, except for the PVT (median), with standard deviation (SD) in
516 parentheses. Gender was determined by asking what gender the participant identified with the
517 most. Morningness/Eveningness (M/E) was included as an exploratory variable (i.e., not included
518 in registration) to assess age-related differences in circadian preferences and was defined on a 5-
519 point Likert scale (i.e., 1 = extreme morning person, 5 = extreme evening person). The average
520 time of testing reflects the start of FTT practice during the respective session, and is specified in
521 24-hour time notation, with the SD in minutes. The offline period represents the time period
522 between the end and start of practice of the test and retest runs of the FTT, respectively. Sleep
523 quality was defined on a 6-point Likert scale (i.e., 1 = very bad, 6 = very good). SSS = Stanford
524 Sleepiness Scale (Maclean et al., 1992), with higher numbers indicative of increased sleepiness.
525 The PVT score indicates the median simple RT across the 30 trials included in the analyses. The
526 p-values resulted from independent samples t-tests or Mann-Whitney U-test assessing group
527 differences, depending on whether the assumption of normality was met or violated, respectively.
528 See Appendix 2 for full statistical output.

529

530 *3.2 Behavioral results*

531 The full sample (n = 22 children, 23 adults) was included in the behavioral analyses. Two children
532 were excluded from statistical contrasts including training 2 (see Appendix 1 for details).

533

534 3.2.1 Learning dynamics

535 Normalized performance measures from all FTT runs are depicted in Figure 2 and the full
536 statistical output can be found in Appendix 3. Here, we provide a review of the key results with a
537 focus on normalized performance speed, as performance accuracy remained relatively stable
538 across practice blocks and largely comparable between age groups (see Figure 2B). Normalized
539 transition time across training runs showed a non-significant trend towards a group x training run
540 x block interaction effect ($F_{(5.27,221.14)} = 2.14$, $p = 0.058$, $\eta^2 = 0.009$, $BF_{10} = 0.020$). Follow-up
541 ANOVAs within each training run indicated significant main effects of group (run 1: $F_{(1,43)} = 8.85$,
542 $p = 0.005$, $\eta^2 = 0.107$, $BF_{10} = 6.661$; run 2: $F_{(1,42)} = 4.10$, $p = 0.049$, $\eta^2 = 0.064$, $BF_{10} = 0.929$) and
543 block in both runs (run 1: $F_{(5.80, 249.41)} = 26.08$, $p < 0.001$, $\eta^2 = 0.202$, $BF_{10} = 1.414$; run 2: $F_{(4.27,179.43)}$
544 $= 3.43$, $p = 0.008$, $\eta^2 = 0.024$, $BF_{10} = 8685.588$). There was no significant group x block interaction
545 effect in either run (both $p > 0.14$; see Appendix 3 for details). These results indicate that
546 performance speed improved across practice blocks within each training run, with slower
547 performance in children but similar performance changes across blocks in the two age groups.

548

549 During the post-learning test, normalized speed showed no credible evidence for effects of group,
550 block or a group x block interaction effect (all $p > 0.13$; full output provided in Appendix 3). These
551 results indicate that children and adults showed comparable performance at the end of training and
552 prior to assessing macro-offline consolidation.

During the retest, normalized performance speed showed a significant main effect of block ($F_{(2.48,106.72)} = 4.91$, $p = 0.005$, $\eta^2 = 0.017$, $BF_{10} = 5171.154$), but no group ($F_{(1,43)} = 0.03$, $p = 0.873$, $\eta^2 < 0.001$, $BF_{10} = 0.493$) or group x block interaction ($F_{(2.48,106.72)} = 0.97$, $p = 0.398$, $\eta^2 = 0.003$, $BF_{10} = 0.037$). These results collectively suggest that children and adults demonstrated comparable improvements in performance speed as a function of practice during the retest.

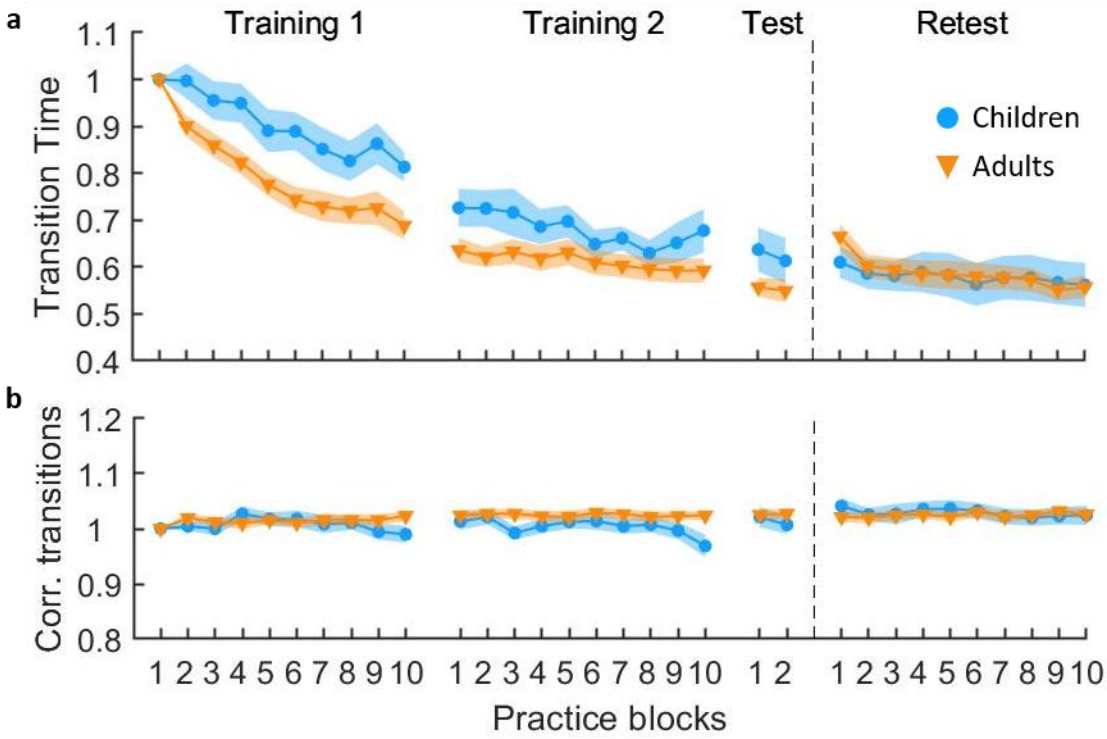

Figure 2. Normalized motor performance across FTT task runs. Measures of movement speed (median normalized transition time; panel **a**) and accuracy (normalized percentage of correct transitions; panel **b**) for the training, test and retest runs. Shaded regions represent standard errors of the mean. n = 22 for children and n = 23 for adults for all task runs, except training 2 (n = 21 children). The main text provides primary statistical information of interest but see Appendix 3 for complete statistical output.

570 3.2.2 Micro-learning across training

571 Micro-online and -offline performance changes are depicted in Figure 3. Panels a and b show the
572 cumulative sums of these performance changes as a function of practice blocks (i.e., values of
573 block n show the sums of the gain values from block 1 through block n). Age group by training
574 run ANOVAs were conducted on the average micro-online and -offline performance changes
575 across task blocks or rest intervals, respectively (Panels c and d in Figure 3). For micro-online
576 performance changes, the group x training run interaction was not significant ($F_{(1,43)} < 0.01$, $p =$
577 0.971, $\eta^2 < 0.001$, $BF_{10} = 0.287$). There was, however, a significant main effect of group, with
578 greater overall micro-online performance changes for adults as compared to children ($F_{(1,43)} = 4.46$,
579 $p = 0.040$, $\eta^2 = 0.058$, $BF_{10} = 1.416$). Additionally, training run 2 demonstrated greater (i.e., less
580 negative) micro-online performance changes than training run 1 ($F_{(1,43)} = 4.80$, $p = 0.034$, $\eta^2 =$
581 0.044, $BF_{10} = 2.039$). The assessment of micro-offline learning showed no group x training run
582 interaction ($F_{(1,43)} = 0.00$, $p = 0.963$, $\eta^2 < 0.001$, $BF_{10} = 0.300$). While the magnitudes of micro-
583 offline performance changes were larger in children as compared to adults, this effect was a non-
584 significant trend ($F_{(1,43)} = 3.70$, $p = 0.061$, $\eta^2 = 0.044$, $BF_{10} = 0.869$). A main effect of training run
585 was present, with micro-offline performance changes being larger in training run 1 as compared
586 to training run 2 ($F_{(1,43)} = 7.99$, $p = 0.007$, $\eta^2 = 0.080$, $BF_{10} = 12.154$). Although children showed
587 quantitatively larger and smaller micro-online and micro-offline gains, respectively, these results
588 should be interpreted with caution. Between group differences in micro-offline learning did not
589 reach statistical significance (i.e., $p = 0.061$) and the reported Bayes Factors for age group
590 differences in both micro-online and -offline performance changes can be considered small (i.e.,
591 < 1.5).

592

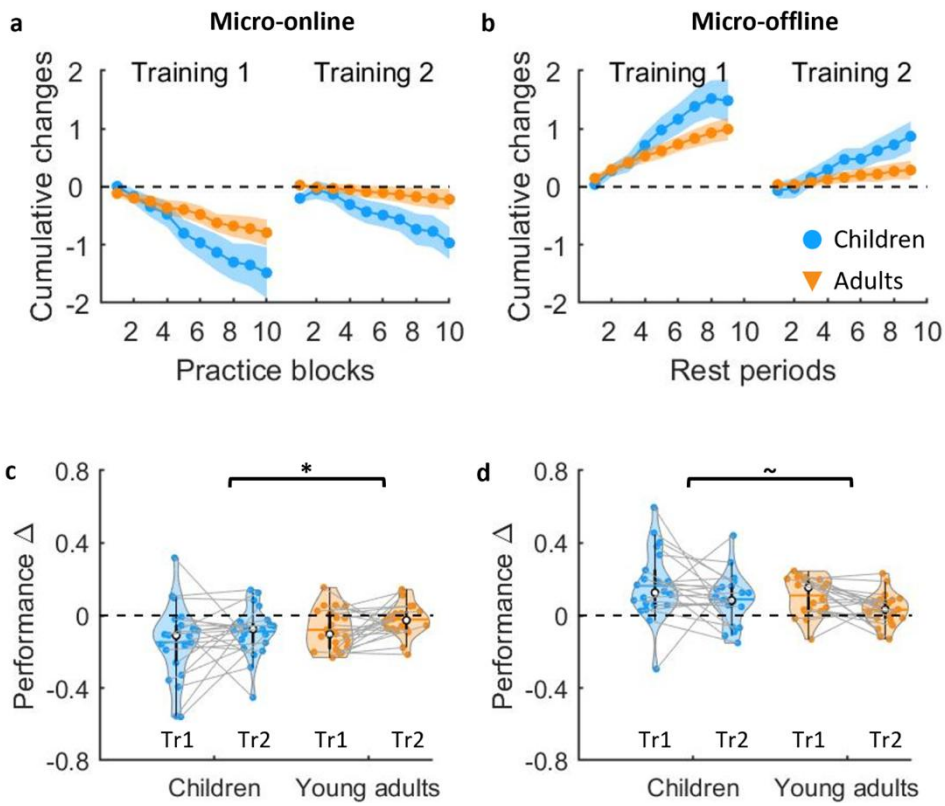

Figure 3. Micro-online (**left**) and micro-offline (**right**) performance changes. The top panels depict the cumulative sums of the micro-online (**a**) and micro-offline (**b**) performance changes across practice/rest epochs for children and adults. Shaded regions represent standard errors of the mean. The bottom panels contain violin plots of micro-online (**c**) and -offline (**d**) gains averaged across blocks for Training Runs 1 and 2 (Tr1 and Tr2, respectively). Positive values are indicative of performance improvements. Shaded regions represent the kernel density estimates of the data, colored circles depict individual data, open circles represent group median, and the horizontal lines depict group means (Bechtold et al., 2021). * $p < 0.05$ and ~ $p < 0.1$ for group differences across the two training runs. n = 22 during training 1 and n = 21 during training 2 for children. n = 23 for adults.

3.2.2 Macro-offline performance changes

Age group differences in macro-offline performance changes are depicted in Figure 4. Analyses revealed that children, as compared to adults, exhibited larger macro-offline changes in both performance speed ($t_{43} = 2.059$, $p = 0.023$, $G = 0.60$, $BF_{10} = 1.573$) and accuracy ($t_{28.685} = 2.527$, $p = 0.009$, $G = 0.74$, $BF_{10} = 3.812$). For completeness, we conducted an exploratory analysis on the magnitude of offline gains using an often-used dependent measure (Dan et al. 2015; King et

al. 2016) that combines speed and accuracy measures into a single metric (global performance index – GPI). Children demonstrated greater offline gains in GPI as compared to adults (depicted Appendix 3; $t_{43} = 2.583$, $p = 0.007$, $G = 0.76$, $BF_{10} = 4.233$). Collectively, these results demonstrate that children exhibited greater macro-offline performance changes than adults, a finding that is in line with our previous work (Van Roy et al., 2024).

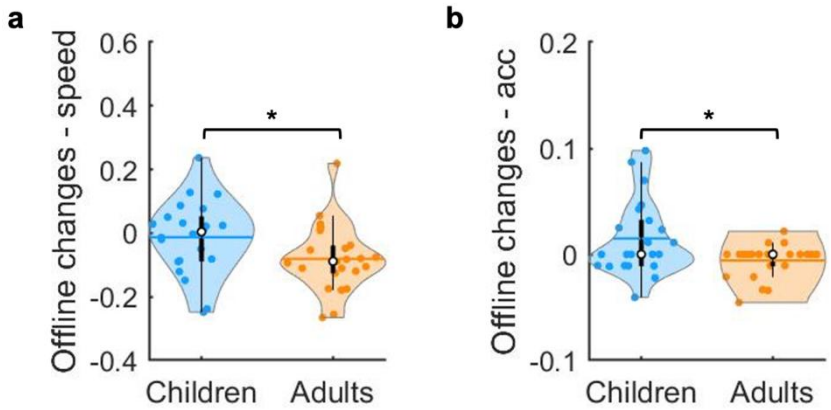

Figure 4. Macro-offline performance changes. Offline changes in normalized speed (**panel a**) and accuracy (**panel b**) across the 5-hour offline period for children and adults. Positive values are indicative of performance improvements from end of training to the 5-hour delayed retest (i.e., larger values reflect enhanced offline consolidation). Shaded regions represent the kernel density estimates of the data, colored circles depict individual data, open circles represent group medians, and the horizontal lines depict group means (Bechtold et al., 2021). * $p < 0.05$ for group differences. n = 22 for children and n = 23 for adults.

3.3 Functional neuroimaging results

The main text focuses on differences between age groups in brain activation during initial learning (i.e., training 1) and changes in activity from training 2 to retest (i.e., across the macro-offline period), as well as their relationship with behavioral performance measures. Results pertaining to brain activity during training 2 and retest, and activity changes from training 1 to training 2 are presented in Appendix 5.

633 3.3.1 Brain activity during early learning

634 Age group differences in the recruitment of brain regions during initial learning (i.e., training 1)
635 were assessed by comparing children and adults in the main effect of task practice (interleaved rest
636 as the implicit baseline; see Figure 5; corresponding results presented in Table 2a). Results
637 revealed that adults exhibited greater activity in a large cluster with an activation peak in the right
638 superior parietal cortex. This cluster extended into the primary motor cortex (M1), postcentral
639 gyrus, supplementary motor area, and cerebellum. Additionally, adults also demonstrated greater
640 activity in a cluster with an activation peak in the right thalamus that extended into the putamen
641 and globus pallidus. Visual inspection of the extracted beta estimates (Figure 5a) as well as the
642 results from the within-group, follow-up analyses (see Appendix 5) revealed that the primary
643 motor cortex, postcentral gyrus, supplementary motor area and cerebellum exhibited significant
644 activations in both age groups (although greater in magnitude in adults). The superior parietal
645 gyrus, thalamus, putamen and globus pallidus showed significant task activity in adults, whereas
646 extracted beta estimates approximated 0 in children (i.e., no differences between task and rest
647 epochs). And lastly, the parahippocampus was significantly deactivated (rest > task) in both age
648 groups, with greater deactivation in children relative as compared to young adults.

649

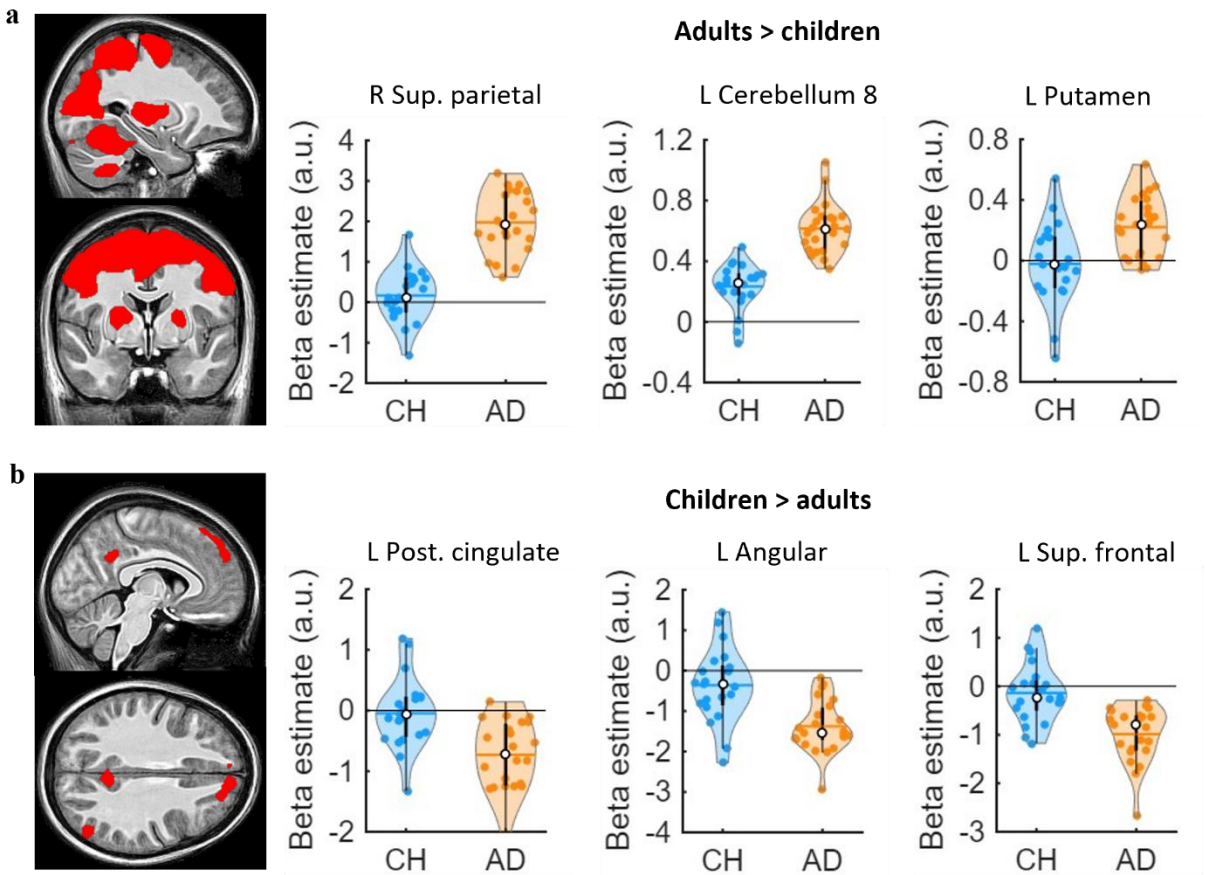

Figure 5. Brain regions showing a significant difference in task-related brain activity between children and adults. **(a)** Adults (AD) > children (CH) contrast. Left images are centered on the L putamen [-26 -1 6]. R sup. parietal = [18 -62 55], L cerebellum 8 = [-20 -60 -48]. **(b)** CH > AD contrast. Left images are centered on the L posterior cingulate peak [-5 50 32]. L angular = [-50 -68 32], L sup. frontal = [-20 42 40]. Statistical images are thresholded at $p_{uncorrected} < 0.001$. x, y and z coordinates are specified in MNI space. Violin plots depict extracted parameter (beta) estimates for selected regions of interest. Shaded regions represent the kernel density estimates of the data, colored circles depict individual data, open circles represent group medians, and the horizontal lines depict group means (Bechtold et al., 2021).

Table 2. Results of task-related activity during early learning (i.e., Training 1).

Area	x	y	z	T	$P_{FWE-SVC}$
a. [Training 1]					
a1. Children - adults					
L Superior frontal	-20	42	40	4.47	0.001*
	-12	32	55	4.1	0.003*
L Angular	-50	-68	32	4.04	0.003*
	-45	-75	40	3.64	0.008*
L Posterior cingulate	-5	-50	32	3.84	0.005*
L Middle frontal	-38	20	50	3.73	0.007*
a2. Adults - children					
R Superior parietal	18	-62	55	8.29	< 0.001*
R Cerebellum 6	22	-55	-20	8.02	< 0.001*
L Cerebellum 8	-20	-60	-48	7.96	< 0.001*
R Thalamus	22	-18	-2	6.30	< 0.001*
R Parahippocampus	32	-20	-25	4.32	0.001*
b. [Training 1 x macro-offline performance changes]					
b1. Children - adults					
R Middle frontal	52	45	5	6.17	< 0.001*
	48	52	8	5.32	< 0.001*
L Parahippocampus	-18	-30	-18	5.05	< 0.001*
L Postcentral	-25	-38	58	5.20	< 0.001*
Extends into R hippocampus					
R Cerebellum 9	15	-42	-42	4.42	0.001*
L Precentral	-50	5	38	3.84	0.006
L Middle frontal	-50	12	45	3.60	0.010
L Inferior frontal, triangular	-55	18	25	3.63	0.010
L Amygdala	-25	0	-18	3.71	0.008
R Supramarginal	52	-35	32	3.61	0.010
	55	-42	38	3.48	0.014
R Superior frontal	30	52	20	3.61	0.010
	25	48	30	3.46	0.014
L Supplementary motor area	-5	20	55	3.45	0.015
R Cerebellum crus 1	42	-68	-35	3.53	0.012
b2. Adults - children					
No suprathreshold clusters					

Table presents clusters at $p_{FWE-SVC} < 0.05$ after family-wise error (FWE), small volume correction (SVC, 10 mm radius) for multiple comparisons. Voxels that were located outside of grey matter and that did not survive SVC are not reported. * $p < 0.05$, Holm-Bonferroni corrected. Minimum cluster size = 5 voxels. x, y and z coordinates are specified in MNI space. Results presented in this table are based on n = 21 children and 23 adults. Results of the within- and across-group contrasts are provided in Appendix 5 for completeness.

In contrast to the results described above, children exhibited greater activity as compared to adults in the left middle and superior, left angular, and left posterior cingulate gyri (Figure 5B). Visual inspection of the beta estimates indicated that these regions were deactivated in adults (i.e., more activity during the rest as compared to task periods), whereas children showed parameter estimates approximating zero.

We then conducted regression analyses assessing the link between brain activation during early training (i.e., training 1; see Appendix 5 for regressions with training 2 activity) and the behavioral performance measures, and whether this differed between age groups. Results revealed no significant age group differences in the relationship between activity during early learning and *micro*-online and -offline performance changes (see Appendix 5).

For *macro*-offline performance changes, the regression analyses showed significant group differences in a large cluster with an activation peak in the left parahippocampus (Figure 6, Table 2b). This cluster extended into the hippocampus, thalamus, caudate nucleus, bilateral primary motor cortices, postcentral gyrus, right supplementary motor area, bilateral middle and posterior cingulate gyri and paracentral lobule. Additionally, group differences were observed in the middle frontal gyrus, left inferior and right superior frontal gyri, left M1, right supramarginal gyrus, left amygdala, and cerebellum. The extracted parameter (beta) estimates revealed that task-related activity in most of these regions was positively related to macro-offline performance changes *within* children, whereas adults either showed the opposite pattern (i.e., negative relationship) or no association.

Altogether, results concerning training 1 revealed that children exhibited less activation as compared to adults across a widespread set of brain regions that included cortical (i.e., superior parietal cortex, M1, postcentral gyrus, SMA) and subcortical (i.e., thalamus, putamen and globus pallidus) motor regions as well as the cerebellum. Furthermore, activations during early learning in the dorsolateral prefrontal cortex, sensorimotor cortex, supramarginal gyrus, cingulate gyrus, amygdala, caudate, (para)hippocampus, thalamus and cerebellum were positively related to macro-offline performance improvements in children.

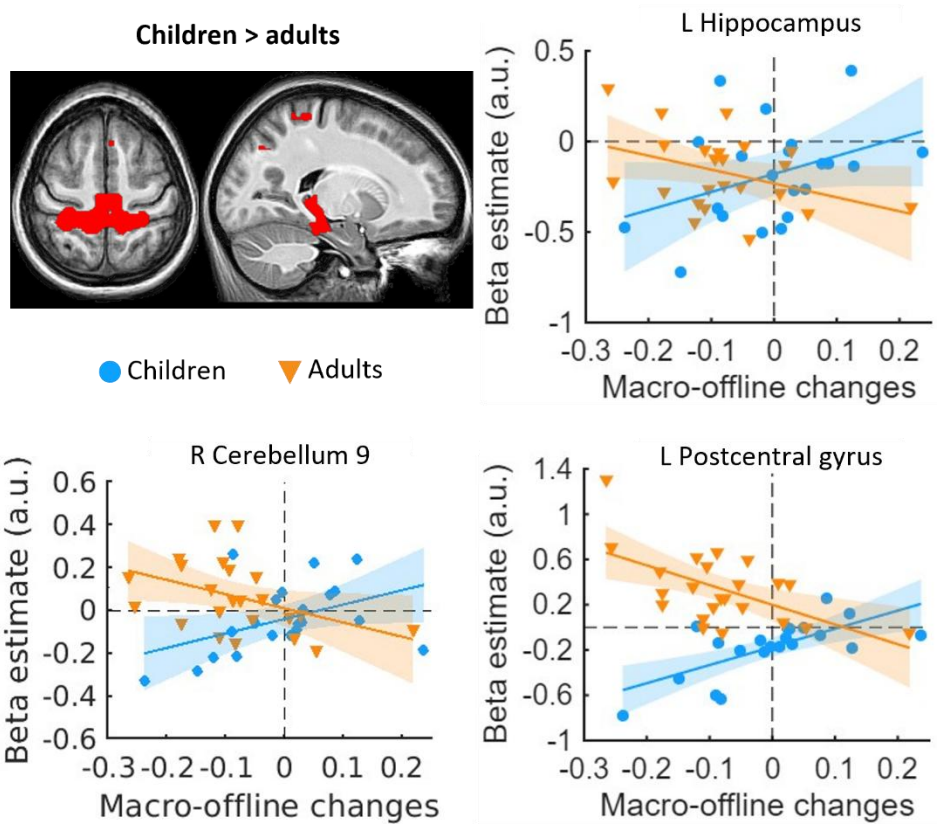

Figure 6. Brain regions showing significant age group differences in the relationship between task-related brain activity during training 1 and macro-offline performance changes. Children > adults contrast. Left brain image is centered on the L postcentral peak [-25 -38 58]. Right brain image is centered on the L hippocampus [-19 -27 -11]. R cerebellum 9 = [15 -42 -42]. Statistical images are thresholded at $p_{uncorrected} < 0.001$. Extracted parameter (beta) estimates for selected regions of interest are plotted as a function of macro-offline performance changes. x, y and z coordinates are specified in MNI space. Shaded regions represent the 95% confidence intervals.

3.3.2 Changes in brain activity from training 2 to retest

As outlined in our registration, changes in brain activity across the 5-hour macro-offline period were examined by contrasting training 2 and retest (Figure 7, Table 3a). Results revealed significant group differences in inter-session changes in activity in the bilateral cerebellum (i.e., left cerebellum crus I, bilateral cerebellum 4-5, right cerebellum 9), right M1 and left hippocampus. Inspection of the beta estimates indicated that these group by session interactions were largely due to a decrease in activity in the left hippocampus in children from training 2 to retest, whereas adults demonstrated inter-session increases in the right M1 and cerebellum. Children also exhibited a slight decrease in activity in cerebellum crus I.

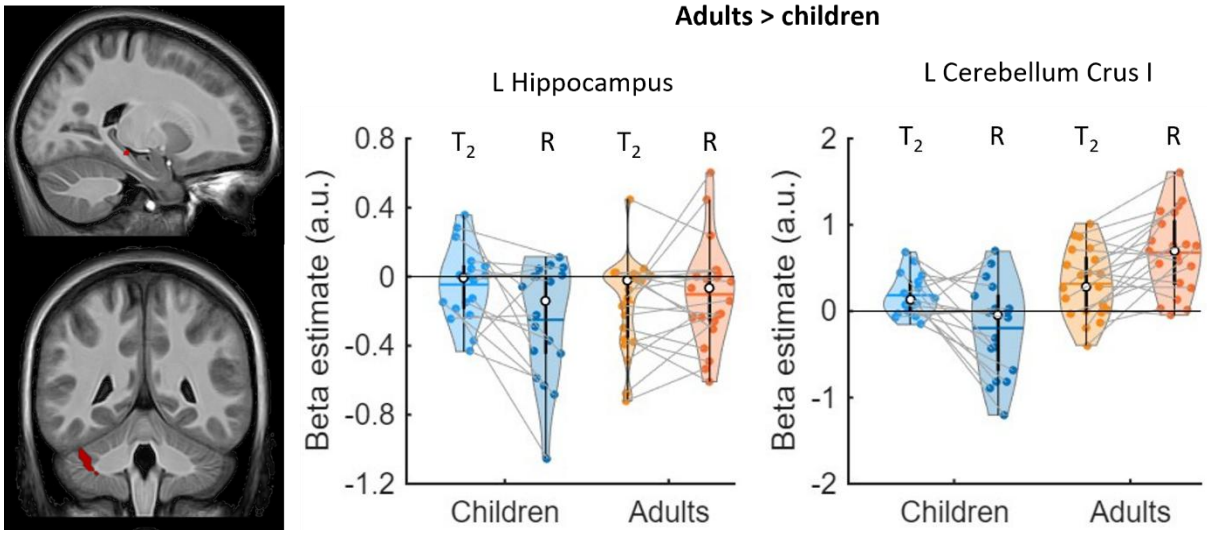

Figure 7. Brain regions showing significant age group differences in the inter-session changes in activity from training 2 to retest. Adults > children contrast. Left images are centered on the L hippocampus peak [-20 -28 -12] (top) and L cerebellum crus I peak [-40 -45 -35] (bottom). Statistical images are thresholded at $p_{uncorrected} < 0.001$. x, y and z coordinates are specified in MNI space. Violin plots depict extracted parameter (beta) estimates for selected regions of interest. Shaded regions represent the kernel density estimates of the data, colored circles depict individual data, open circles represent group medians, and the horizontal lines depict group means (Bechtold et al., 2021). T_2 = Training 2. R = Retest.

Table 3. Changes in task activity from training 2 to retest [Retest – Training 2]

Area	x	y	z	T	$P_{FWE-SVC}$
a. [Retest – Training 2]					
a1. Children - adults					
No suprathreshold clusters					
a2. Adults - children					
L Cerebellum crus 1	-40	-45	-35	4.48	0.001*
R Precentral	15	-22	70	3.59	0.006*
R Cerebellum 9	8	-52	-52	3.54	0.010*
R Cerebellum 4-5	10	-48	-10	3.52	0.010*
L Cerebellum 4-5	-10	-48	-12	3.45	0.012*
L Hippocampus	-20	-28	-12	3.33	0.016*
b. [(Retest – Training 2) x macro-offline performance changes]					
b1. Children - adults					
No suprathreshold clusters					
b2. Adults - children					
L Precuneus[+]	-20	-62	30	4.63	< 0.001*
R Superior frontal	22	12	42	4.31	0.002*
L Putamen	-30	0	10	3.62	0.009
L Precentral	-32	2	48	3.84	0.005
L Middle cingulate	-12	-35	45	3.76	0.007
R Precuneus	8	-52	62	3.44	0.014
R Caudate	5	8	-2	3.18	0.014
R Inferior frontal, opercular	60	12	12	3.73	0.007
R Precentral	35	0	40	3.42	0.014
L Inferior frontal, triangular	-35	30	18	3.35	0.017
R Anterior orbital	20	28	-12	3.51	0.012
R Hippocampus/Parahippocampus	30	-32	-10	3.47	0.013
L Paracentral lobule	-8	-38	62	3.41	0.015
R Supramarginal	58	-30	30	3.40	0.015

Table presents clusters at $p_{FWE-SVC} < 0.05$ after family-wise error (FWE), SVC for multiple comparisons. Voxels that were located outside of gray matter and that did not survive small volume correction (SVC, 10 mm radius) are not reported. * $p < 0.05$, Holm-Bonferroni corrected. Minimum cluster size = 5 voxels. x, y and z coordinates are specified in MNI space. [+] Cluster peak was located in white matter but extended into several gray matter regions. Results presented in this table are based on n = 18 children and 23 adults. Results of the within- and across-group contrasts are provided in Appendix 5.

We then assessed whether changes in brain responses from training 2 to the 5-hour retest were related to the macro-offline performance changes. Results revealed that inter-session changes in activity in the bilateral inferior and right superior frontal gyri, left middle cingulate gyrus, bilateral M1, left paracentral lobule, right supramarginal gyrus, bilateral precuneus, left putamen, right caudate nucleus, and right hippocampus/parahippocampus were differentially related to the macro-offline performance changes between the two groups (Figure 8, Table 3b). Inspection of the beta estimates was conducted to decompose these effects and revealed that greater decreases in activity from training 2 to retest in the left inferior and right superior frontal gyrus, left middle cingulate gyrus, left paracentral lobule, precuneus, left putamen, right caudate and right hippocampus were related to greater macro-offline performance changes *within* children, whereas no relationships were observed within adults.

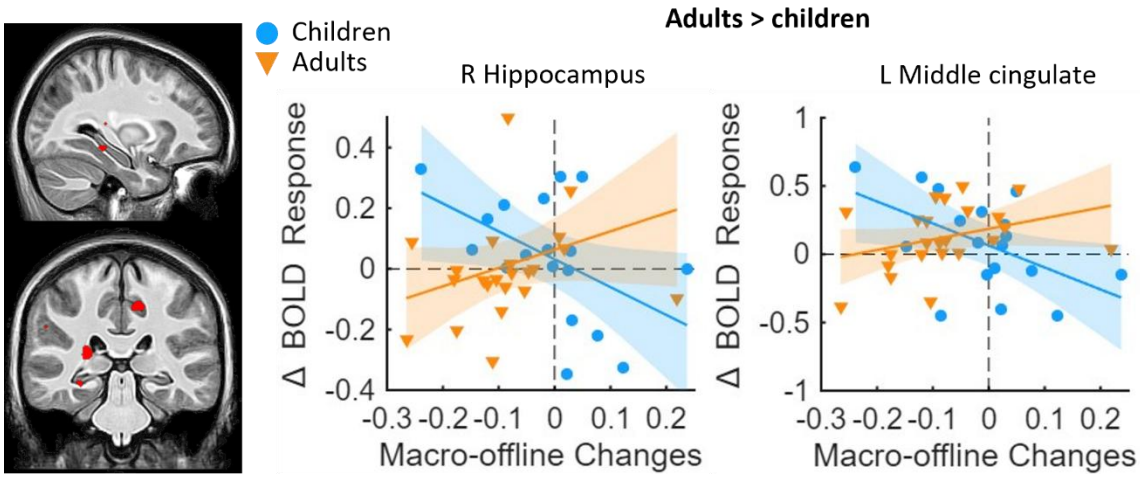

Figure 8. Brain regions showing significant age group differences in the relationship between inter-session changes (retest – training 2) in activity and macro-offline performance changes. Adults > children contrast. Left image is centered on the R hippocampus peak [30 -32 -10]. L middle cingulate = [-12 -35 45]. Statistical images are thresholded at $p_{uncorrected} < 0.001$. Extracted parameter (beta) estimates that represent inter-session changes in activity for selected regions of interest are plotted as a function of macro-offline performance changes. x, y and z coordinates are specified in MNI space. Shaded regions represent the 95% confidence intervals.

Taken together, children exhibited decreases in activity in the left hippocampus from training 2 to retest on the motor sequence, whereas adults showed inter-session increases in the right M1 and cerebellum. Moreover, greater inter-session decreases in activity in prefrontal cortex, hippocampus and the putamen were associated with larger macro-offline performance changes in children.

4. Discussion

The current study employed task-related fMRI to identify the neural correlates of MSL in children, including the developmental advantage in wake-related offline motor memory consolidation. The behavioral results reproduced our previously shown childhood benefit in awake macro-offline motor memory consolidation (Van Roy et al. 2024). Neuroimaging results revealed that: (1) children exhibited less activation as compared to adults during early training across a widespread set of brain regions that included cortical (i.e., superior parietal cortex, M1, postcentral gyrus, SMA) and subcortical (i.e., thalamus, putamen and globus pallidus) regions as well as the cerebellum; (2) there was a positive relationship between macro-offline performance improvements in children and activity during early learning in the dorsolateral prefrontal cortex, sensorimotor cortex, supramarginal gyrus, cingulate gyrus, amygdala, caudate, (para)hippocampus, thalamus and cerebellum; (3) children exhibited decreases in activity in the hippocampus from late initial learning to the retest, whereas adults showed inter-session increases in the M1 and cerebellum; and, (4) greater inter-session decreases in activity in prefrontal cortex, hippocampus and the putamen were associated with larger macro-offline performance changes in children.

779 The discussion below focuses on the interpretation of the primary differences between children
780 and adults. Appendix 6 includes supplementary discussions on the behavioral results assessing
781 initial learning dynamics (section 6.1), micro-offline performance changes (section 6.2), the
782 relationship between brain activity during initial learning and micro-offline performance (section
783 6.4), and the inter-session changes in brain activity in adults (section 6.5).

784 *4.1 Children exhibit a behavioral advantage in awake memory consolidation*

785 Behavioral results of the current research revealed that macro-offline consolidation was enhanced
786 in children, as evidenced by their larger performance changes in both speed and accuracy across
787 the 5-hour macro-offline period. While adults exhibited a deterioration in performance (i.e., offline
788 performance changes were significantly smaller than zero; see Appendix 3), children maintained
789 their performance level over the 5-hour interval. This childhood advantage is consistent with the
790 larger 5-hour performance changes in speed that we previously observed in children (Van Roy et
791 al., 2024) as well as the enhanced offline consolidation in children reported by other researchers
792 (Ashtamker & Karni, 2013; Beck et al., 2024; Voisin et al., 2024). Accordingly, our results add to
793 the body of evidence demonstrating that children exhibit superior offline consolidation of acquired
794 motor sequences across a post-learning period of wakefulness.

795

796 *4.2 Children exhibit smaller modulations in brain activity between task and rest than adults*

797 Analyses assessing age group differences during initial training (i.e., training 1) revealed that
798 adults exhibited greater activation as compared to children across a widespread set of brain regions
799 that included cerebellar, cortical and subcortical areas. Follow-up, within-group contrasts and
800 visual inspection of the extracted beta estimates revealed that these between-group differences

801 could be decomposed into different patterns of results. First, both children and adults showed
802 significant activations of cerebellar and motor regions (i.e., superior parietal cortex, M1,
803 postcentral gyrus, SMA) known to be involved in motor task performance, yet the magnitude of
804 these activations was smaller in children. This result is partially consistent with the findings of
805 Thomas et al. (2004), which observed greater cortical activation in adults as compared to children.
806 One could argue that the reduced cortical activation in children may reflect the ongoing
807 development of the cerebral cortex (i.e., cortical thinning and myelination; Kwon et al., 2020;
808 Muftuler et al., 2011; Østby et al., 2009), as prior research in 8- to 18-year-old children has found
809 positive relationships between the maturation of white matter and brain activation in task-relevant
810 regions during a working memory task (Olesen et al., 2003). An alternative explanation is that the
811 reduced activation of these areas during task practice in children may stem from greater
812 engagement during the interleaved rest periods that serve as the baseline condition in the univariate
813 fMRI block design. In other words, the involvement of these regions *during active task practice*
814 may be relatively comparable between the two age groups, but the engagement of these regions
815 *during interleaved rest* is greater in children. These two alternatives cannot be disentangled with
816 the employed analytic approaches.
817
818 The second pattern that contributed to the overall greater activation in adults as compared to
819 children was predominantly located in subcortical regions. Specifically, adults showed significant
820 activation of the thalamus, putamen and globus pallidus, whereas children exhibited parameter
821 estimates that approximated zero (i.e., the magnitude of activity was similar in task and rest). The
822 lack of significant activations in children could simply be the result of these regions not being
823 recruited during task practice (nor in interleaved rest). Alternatively, it could be that these regions

824 are indeed recruited, but equivalently across task and rest epochs. Regardless of these competing
825 explanations, these data are not in line with those presented in Thomas et al. (2004), which
826 observed greater activation of subcortical regions in children relative to adults. Similarly, other
827 developmental studies also demonstrated significant recruitment of the putamen and thalamus
828 during a motor sequence learning task in children (Hedenius & Persson, 2022; Sharer et al., 2015).
829
830 Analyses of age group differences during early training also revealed group differences in the
831 activation of a subset of brain regions commonly associated with the default mode network
832 (DMN), including the middle and superior frontal, angular, and posterior cingulate gyri. Follow-
833 up, within-group contrasts and visual inspection of the extracted beta estimates indicated that these
834 between-group differences were the result of greater deactivation in adults as compared to
835 children. These results in adults align with the well-established decreased DMN activity during
836 task practice as compared to rest (Raichle, 2015). Furthermore, the differences between children
837 and adults are consistent with previous research that observed developmental increases in brain
838 deactivation during a repetitive button-press task (Morita et al., 2019). As the DMN has been
839 associated with mind-wandering and other inward-directed cognition in adults (Buckner &
840 DiNicola, 2019; Christoff et al., 2009), one could speculate that children disengage from the task
841 less during the short rest periods and thus, show less deactivation of the DMN during task as
842 compared to rest.
843
844 Altogether, results suggest that children exhibit smaller modulations in brain activity between task
845 and rest epochs. Based on this finding, we speculate that the child's brain may stay more engaged
846 during the short rest breaks relative to adults. Several potential explanations could contribute to

847 this continued engagement of the developing brain during interleaved rest, including active
848 consolidation processes (Buch et al., 2021; Gann et al., 2023), the increased need of executive
849 functions to lay stay still in the scanner (Camacho et al., 2020), or cognitive preparation for the
850 upcoming practice block (Camacho et al., 2020). Appendix 6 (section 6.3) provides a more
851 extensive discussion of these possibilities. Although the current experimental design and analytic
852 approach do not allow us to distinguish between these various possible explanations, our results
853 do suggest that brain activity during the interleaved rest epochs – as opposed to solely during task
854 practice - may contribute to the observed age-related differences.

855 *4.3 The relationship between functional activity during training 1 and offline performance changes*
856 As the current study aimed to identify the functional neural correlates underlying the childhood
857 advantage in offline processing, we conducted regression analyses that assessed the relationship
858 between brain activation during initial training (i.e., training 1) and the behavioral macro-offline
859 performance changes. Group differences were observed between children and young adults, which
860 were largely driven by a positive relationship between macro-offline performance changes and
861 functional activity during early training in the dorsolateral prefrontal cortex, sensorimotor cortex,
862 supramarginal gyrus, cingulate gyrus, amygdala, caudate, (para)hippocampus, thalamus and
863 cerebellum in children.
864
865 The sensorimotor cortex has been shown to be involved in the acquisition of a motor sequence in
866 both pediatric (Hedenius & Persson, 2022; Mostofsky et al., 2006) and adult (Albouy et al., 2015;
867 Dolfen et al., 2021; Nicolas et al., 2025) populations, a result that was replicated in the current
868 study. Visual inspection of the positive brain-behavior relationships revealed that greater activity

in these regions during task practice relative to rest was associated with greater macro-offline performance changes.

Activity in the DLPFC, caudate nucleus, (para)hippocampus, supramarginal gyrus and cerebellum crus I were also positively related to the macro-offline performance changes in children. Prior research in adults has demonstrated that the prefrontal and parietal regions as well as the caudate nucleus, (para)hippocampus and cerebellum crus I are recruited during the early phase of initial practice that requires high cognitive control (Albouy et al., 2013; Doyon et al., 2002; Hikosaka et al., 2002). Activity in these regions typically decreases as a function of practice, when the participant becomes more proficient at performing the motor sequence. This suggests that enhanced macro-offline consolidation in children may be linked to higher activation of brain regions that are engaged early in the learning process and under high cognitive control. Moreover, the early engagement of the hippocampus has been thought to play a key role in forming the abstract representation of a motor sequence, which is encoded in spatial coordinates (i.e., organization of the stimuli in space outside of the individual's body) and is effector-independent (i.e., irrespective of the effector involved in the execution; Albouy et al., 2015; Doyon, Korman, et al., 2009). This hippocampal activity has previously been shown to predict subsequent consolidation across a period of sleep in adults (Albouy et al., 2008). It is thus tempting to speculate that greater macro-offline performance changes in children are associated with the development of an abstract representation of the motor sequence during early training.

Interestingly, visual inspection of the positive relationships in the hippocampus, supramarginal gyrus and DLPFC revealed that smaller and larger macro-offline performance changes were linked

892 to beta estimates that were negative or approximated zero, respectively. Accordingly, significant
893 deactivation of these regions during active task practice was detrimental for offline consolidation
894 in children. Conversely, similar activations during task practice and rest (i.e., beta estimates
895 approximating 0) were beneficial for consolidation. This suggests that similar levels of activity
896 across task and rest epochs - potentially reflecting continued engagement of these regions during
897 interleaved rest - facilitated the childhood advantage in macro-offline motor memory
898 consolidation.

899 *4.4 Inter-session changes in neural activity*

900 The assessment of changes in brain activity across the 5-hour offline period (i.e., from training 2
901 to retest) revealed age group differences in the primary motor cortex, hippocampus and cerebellum
902 (i.e., cerebellum lobule 4-5, lobule 9 and crus I). Specifically, children exhibited significant inter-
903 session decreases in hippocampal activity, whereas adults showed significant increases in
904 activation of M1 and the cerebellum (see Appendix 6 for a discussion of the changes in adults).
905 Moreover, inter-session decreases in activity in the prefrontal cortex, hippocampus and putamen
906 supported larger macro-offline performance changes in children, whereas adults failed to show
907 such relationships.
908

909 The opposing inter-session changes in hippocampal activity between age groups, along with the
910 differing relationships between macro-offline consolidation and inter-session changes in
911 hippocampal and striatal activity, may reflect age-related differences in awake offline motor
912 memory consolidation processes. Specifically, children demonstrated greater decreases in
913 hippocampal activity from training 2 to retest as compared to adults. Furthermore, greater inter-

914 session *decreases* in activity in the hippocampus and striatum were linked to larger performance
915 changes across the macro-offline period in children, suggesting that these decreases at least
916 partially support the enhanced consolidation in children. Whereas Hedenius & Persson, (2022)
917 also observed a negative relationship between hippocampal activity and offline performance
918 changes on a sequential task in children, research in adults has observed the opposite pattern
919 (Albouy et al., 2008; Albouy, Sterpenich, et al., 2013; Walker et al., 2005). Specifically, in adults,
920 the hippocampus and striatum have been shown to increase in activity across offline periods that
921 include sleep. These sleep-dependent increases in activity are usually observed in parallel to the
922 emergence of significant offline performance changes from training to retest. Additionally, striatal
923 activity has also been shown to increase across offline periods of wakefulness, which are
924 accompanied by a maintenance of performance (Albouy et al., 2008; Albouy, Sterpenich, et al.,
925 2013). Based on these findings, we hypothesized that – similar to adults – the enhanced macro-
926 offline performance changes in children would be linked to increases in striatal and hippocampal
927 activity from training 2 to retest. Our observation of the opposite pattern in children suggests that
928 the childhood benefit in macro-offline consolidation is supported by inter-session changes in
929 activity that are distinct from those in adults. Further research is needed to clarify the underlying
930 mechanisms contributing to this uniqueness in the developing brain.

931 *4.6 Limitations and future directions*

932 The current study has limitations that should be considered. *First*, there was a relatively high,
933 although largely expected, exclusion rate of young children (i.e., 6- and 7-year-olds; see flow
934 diagram for inclusion and exclusion in Appendix 1). As a result, we did not acquire task-related
935 imaging data from any 6-year-olds, and 7-year-olds were relatively under-sampled in our

experiment. Future studies could consider adjusting the motor task (e.g., spatially cued task) or implementing certain measures (e.g., additional familiarization in a mock scanner) to increase the number of young children that successfully complete the experiment.

Second, head motion can impact neuroimaging results. As children exhibited more head movement during the scanning (see Appendix 4), it is plausible that the deleterious influence of head motion on the BOLD signal is magnified in this age group (Greene et al., 2018). Although we adopted multiple approaches to minimize the negative impact of head motion (e.g., realignment of BOLD images, exclusion of runs where maximum linear movement exceeded 5 mm and inputting head motion parameters as nuisance regressors), we cannot eliminate the possibility that head motion affected the fMRI results more in children than in adults.

Third, the task design employed in this research does not allow the assessment of whether performance improvements were specific to sequence learning or general improvements in motor performance (e.g., mapping the numbers to the keys, getting better at pressing the keys). Sequence-specific learning is typically assessed by incorporating random trials in the motor task and comparing performance between sequential and random trials (see Van Roy et al., 2024 for an example). Nevertheless, results of our previous study indicated that children indeed exhibited sequence-specific learning (Van Roy et al., 2024), albeit with a smaller magnitude than in adults. Furthermore, the childhood advantage in macro-offline consolidation reported in this earlier work was shown to be specific to strengthening the sequential memory rather than a general improvement. Accordingly, it is likely that the developmental advantage reported in the current research was also specific to the acquired motor sequence.

959

960 *Fourth,* the sample size calculation used in our study registration was based on expected behavioral
961 effect sizes rather than neural outcomes. This choice was largely motivated by the scarcity of
962 pediatric neuroimaging studies that have examined motor learning and memory consolidation
963 processes. Nonetheless, it is worth emphasizing that the magnitudes of task-based fMRI effects
964 may be smaller than behavioral outcomes and thus it is possible that our neuroimaging analyses
965 are under-powered.

966

967 *Fifth*, it is worth explicitly stating that only a subset of the brain regions for which activity linked
968 to the magnitudes of offline gains (i.e., regression analyses reported in Tables 2b and 3b) survived
969 the additional step of Holm-Bonferroni correction performed for the number of clusters.
970 Accordingly, results pertaining to the regions that did not survive this correction should be
971 interpreted with extra caution.

972

973 *Sixth,* there remain several open questions regarding the interpretation of the observed neural
974 activity in children. Future research should systematically manipulate the experimental task or
975 design to determine the specific learning mechanisms that the developing brain prioritizes and
976 supports. For instance, future studies could differentiate between sequence-specific and general
977 motor performance brain activity by incorporating a random task in which the order of the
978 sequence numbers on the screen changes every trial. Additionally, we speculated that children
979 prioritize the encoding of an abstract, spatial representation of the motor sequence. And
980 experimental design like in Albouy et al. (2015) could be implemented in future research to

determine whether the developing brain builds separate spatial and motoric representations of a motor sequence, and then identify the respective underlying neural correlates.

5. Conclusions

The present study provided a comprehensive examination of the behavioral and neural correlates of motor sequence learning and memory consolidation in 7- to 11-year-old children. Behavioral results added to the growing body of evidence suggesting that children exhibit enhanced offline consolidation over epochs of post-learning wakefulness. Results from our task-related fMRI analyses revealed that children exhibited less neural activation during initial motor sequence learning – as compared to interleaved rest intervals – across a widespread network of brain regions, including the striatum, cerebellum and cortical motor areas. We speculate that this smaller activation in children may be – at least partially – attributed to greater engagement of these areas during the interleaved rest periods in children as compared to adults. The enhanced performance improvements across the 5-hour offline period in children were associated with task-related activations during initial sequence learning in frontoparietal, cerebellar, sensorimotor and subcortical regions, as well as inter-session decreases in prefrontal, sensorimotor and subcortical activity. Further investigations into the specific learning mechanisms underlying the neural correlates of motor sequence learning and memory consolidation in children are warranted.

Acknowledgements

This work was supported by internal funds at the University of Utah and a S10 Instrumentation Program Grant awarded to the University of Utah (S10OD026788).

1003 **References**

1004 Adi-Japha, E., Badir, R., Dorfberger, S., & Karni, A. (2014). A matter of time: Rapid motor
1005 memory stabilization in childhood. *Developmental Science*, *17*(3), Article 3.
1006 https://doi.org/10.1111/desc.12132

1007 Albouy, G., Fogel, S., King, B. R., Laventure, S., Benali, H., Karni, A., Carrier, J., Robertson, E.
1008 M., & Doyon, J. (2015). Maintaining vs. enhancing motor sequence memories: Respective
1009 roles of striatal and hippocampal systems. *NeuroImage*, *108*, 423–434.
1010 https://doi.org/10.1016/j.neuroimage.2014.12.049

1011 Albouy, G., King, B. R., Maquet, P., & Doyon, J. (2013). Hippocampus and striatum: Dynamics
1012 and interaction during acquisition and sleep-related motor sequence memory consolidation.
1013 *Hippocampus*, *23*(11), 985–1004. https://doi.org/10.1002/hipo.22183

1014 Albouy, G., Sterpenich, V., Balteau, E., Vandewalle, G., Desseilles, M., Dang-Vu, T., Darsaud,
1015 A., Ruby, P., Luppi, P.-H., Degueldre, C., Peigneux, P., Luxen, A., & Maquet, P. (2008).
1016 Both the Hippocampus and Striatum Are Involved in Consolidation of Motor Sequence
1017 Memory. *Neuron*, *58*(2), 261–272. https://doi.org/10.1016/j.neuron.2008.02.008

1018 Albouy, G., Sterpenich, V., Vandewalle, G., Darsaud, A., Gais, S., Rauchs, G., Desseilles, M.,
1019 Boly, M., Dang-Vu, T., Balteau, E., Degueldre, C., Phillips, C., Luxen, A., & Maquet, P.
1020 (2013). Interaction between Hippocampal and Striatal Systems Predicts Subsequent
1021 Consolidation of Motor Sequence Memory. *PLoS ONE*, *8*(3), e59490.
1022 https://doi.org/10.1371/journal.pone.0059490

1023 Ashtamker, L., & Karni, A. (2013). Motor memory in childhood: Early expression of consolidation
1024 phase gains. *Neurobiology of Learning and Memory*, *106*, 26–30.
1025 https://doi.org/10.1016/j.nlm.2013.07.003

1026 Basner, M., Mollicone, D., & Dinges, D. F. (2011). Validity and sensitivity of a brief psychomotor
1027 vigilance test (PVT-B) to total and partial sleep deprivation. *Acta Astronautica*, *69*(11–12),
1028 949–959. https://doi.org/10.1016/j.actaastro.2011.07.015

1029 Bechtold, B., Fletcher, P., Seamusholden, & Gorur-Shandilya, S. (2021). *bastibe/Violinplot-*
1030 *Matlab: A Good Starting Point* (Version v0.1) [Computer software]. Zenodo.
1031 https://doi.org/10.5281/ZENODO.4559847

1032 Beck, M. M., Kristensen, F. T., Abrahamsen, G., Spedden, M. E., Christensen, M. S., & Lundbye-
1033 Jensen, J. (2024). Distinct mechanisms for online and offline motor skill learning across
1034 human development. *Developmental Science*, *27*(6), e13536.
1035 https://doi.org/10.1111/desc.13536

1036 Bönstrup, M., Iturrate, I., Thompson, R., Cruciani, G., Censor, N., & Cohen, L. G. (2019). A Rapid
1037 Form of Offline Consolidation in Skill Learning. *Current Biology*, *29*(8), 1346-1351.e4.
1038 https://doi.org/10.1016/j.cub.2019.02.049

Boré, A., Guay, S., Bedetti, C., Meisler, S., & GuenTher, N. (2023). *Dcm2Bids* (Version 3.1.1) [Computer software]. Zenodo. https://doi.org/10.5281/ZENODO.8436509

Buch, E. R., Claudino, L., Quentin, R., Bönstrup, M., & Cohen, L. G. (2021). Consolidation of human skill linked to waking hippocampo-neocortical replay. *Cell Reports*, *35*(10), 109193. https://doi.org/10.1016/j.celrep.2021.109193

Buckner, R. L., & DiNicola, L. M. (2019). The brain's default network: Updated anatomy, physiology and evolving insights. *Nature Reviews Neuroscience*, *20*(10), 593–608. https://doi.org/10.1038/s41583-019-0212-7

Camacho, M. C., Quiñones-Camacho, L. E., & Perlman, S. B. (2020). Does the child brain rest?: An examination and interpretation of resting cognition in developmental cognitive neuroscience. *NeuroImage*, *212*, 116688. https://doi.org/10.1016/j.neuroimage.2020.116688

Chen, P.-C., Stritzelberger, J., Walther, K., Hamer, H., & Staresina, B. P. (2024). *Hippocampal ripples during offline periods predict human motor sequence learning*. https://doi.org/10.1101/2024.10.06.614680

Christoff, K., Gordon, A. M., Smallwood, J., Smith, R., & Schooler, J. W. (2009). Experience sampling during fMRI reveals default network and executive system contributions to mind wandering. *Proceedings of the National Academy of Sciences*, *106*(21), 8719–8724. https://doi.org/10.1073/pnas.0900234106

Dan, X., King, B. R., Doyon, J., & Chan, P. (2015). Motor Sequence Learning and Consolidation in Unilateral De Novo Patients with Parkinson's Disease. *PLOS ONE*, *10*(7), e0134291. https://doi.org/10.1371/journal.pone.0134291

Debas, K., Carrier, J., Orban, P., Barakat, M., Lungu, O., Vandewalle, G., Tahar, A. H., Bellec, P., Karni, A., Ungerleider, L. G., Benali, H., & Doyon, J. (2010). Brain plasticity related to the consolidation of motor sequence learning and motor adaptation. *Proceedings of the National Academy of Sciences*, *107*(41), 17839–17844. https://doi.org/10.1073/pnas.1013176107

Dinges, D. F., & Powell, J. W. (1985). Microcomputer analyses of performance on a portable, simple visual RT task during sustained operations. *Behavior Research Methods, Instruments, & Computers*, *17*(6), 652–655. https://doi.org/10.3758/BF03200977

Dolfen, N., King, B. R., Schwabe, L., Gann, M. A., Veldman, M. P., Von Leupoldt, A., Swinnen, S. P., & Albouy, G. (2021). Stress Modulates the Balance between Hippocampal and Motor Networks during Motor Memory Processing. *Cerebral Cortex*, *31*(2), 1365–1382. https://doi.org/10.1093/cercor/bhaa302

Dolfen, N., King, B. R., Schwabe, L., Swinnen, S., & Albouy, G. (2019). Glucocorticoid response to stress induction prior to learning is negatively related to subsequent motor memory

consolidation. *Neurobiology of Learning and Memory*, *158*, 32–41. https://doi.org/10.1016/j.nlm.2019.01.009

Dorfberger, S., Adi-Japha, E., & Karni, A. (2007). Reduced Susceptibility to Interference in the Consolidation of Motor Memory before Adolescence. *PLoS ONE*, *2*(2), Article 2. https://doi.org/10.1371/journal.pone.0000240

Doyon, J., Bellec, P., Amsel, R., Penhune, V., Monchi, O., Carrier, J., Lehéricy, S., & Benali, H. (2009). Contributions of the basal ganglia and functionally related brain structures to motor learning. *Behavioural Brain Research*, *199*(1), 61–75. https://doi.org/10.1016/j.bbr.2008.11.012

Doyon, J., Gabitov, E., Vahdat, S., Lungu, O., & Boutin, A. (2018). Current issues related to motor sequence learning in humans. *Current Opinion in Behavioral Sciences*, *20*, 89–97. https://doi.org/10.1016/j.cobeha.2017.11.012

Doyon, J., Korman, M., Morin, A., Dostie, V., Tahar, A. H., Benali, H., Karni, A., Ungerleider, L. G., & Carrier, J. (2009). Contribution of night and day sleep vs. Simple passage of time to the consolidation of motor sequence and visuomotor adaptation learning. *Experimental Brain Research*, *195*(1), 15–26. https://doi.org/10.1007/s00221-009-1748-y

Doyon, J., Song, A. W., Karni, A., Lalonde, F., Adams, M. M., & Ungerleider, L. G. (2002). Experience-dependent changes in cerebellar contributions to motor sequence learning. *Proceedings of the National Academy of Sciences*, *99*(2), 1017–1022. https://doi.org/10.1073/pnas.022615199

Du, Y., Valentini, N. C., Kim, M. J., Whitall, J., & Clark, J. E. (2017). Children and Adults Both Learn Motor Sequences Quickly, But Do So Differently. *Frontiers in Psychology*, *08*. https://doi.org/10.3389/fpsyg.2017.00158

Esteban, O., Markiewicz, C. J., Blair, R. W., Moodie, C. A., Isik, A. I., Erramuzpe, A., Kent, J. D., Goncalves, M., DuPre, E., Snyder, M., Oya, H., Ghosh, S. S., Wright, J., Durnez, J., Poldrack, R. A., & Gorgolewski, K. J. (2019). fMRIPrep: A robust preprocessing pipeline for functional MRI. *Nature Methods*, *16*(1), 111–116. https://doi.org/10.1038/s41592-018-0235-4

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Fischer, S., Wilhelm, I., & Born, J. (2007). Developmental Differences in Sleep's Role for Implicit Off-line Learning: Comparing Children with Adults. *Journal of Cognitive Neuroscience*, *19*(2), Article 2. https://doi.org/10.1162/jocn.2007.19.2.214

Gann, M. A., Dolfen, N., King, B. R., Robertson, E. M., & Albouy, G. (2023). Prefrontal stimulation as a tool to disrupt hippocampal and striatal reactivations underlying fast motor

memory consolidation. *Brain Stimulation*, *16*(5), 1336–1345. https://doi.org/10.1016/j.brs.2023.08.022

Greene, D. J., Koller, J. M., Hampton, J. M., Wesevich, V., Van, A. N., Nguyen, A. L., Hoyt, C. R., McIntyre, L., Earl, E. A., Klein, R. L., Shimony, J. S., Petersen, S. E., Schlaggar, B. L., Fair, D. A., & Dosenbach, N. U. F. (2018). Behavioral interventions for reducing head motion during MRI scans in children. *NeuroImage*, *171*, 234–245. https://doi.org/10.1016/j.neuroimage.2018.01.023

Hedenius, M., & Persson, J. (2022). Neural correlates of sequence learning in children with developmental dyslexia. *Human Brain Mapping*, *43*(11), 3559–3576. https://doi.org/10.1002/hbm.25868

Hikosaka, O., Nakamura, K., Sakai, K., & Nakahara, H. (2002). Central mechanisms of motor skill learning. *Current Opinion in Neurobiology*, *12*(2), 217–222. https://doi.org/10.1016/S0959-4388(02)00307-0

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, *6*, 65–70.

Iida, Y., Miyazaki, M., & Uchida, S. (2010). Developmental changes in cognitive reaction time of children aged 6–12 years. *European Journal of Sport Science*, *10*(3), Article 3. https://doi.org/10.1080/17461390903515162

Ismail, F. Y., Fatemi, A., & Johnston, M. V. (2017). Cerebral plasticity: Windows of opportunity in the developing brain. *European Journal of Paediatric Neurology*, *21*(1), 23–48. https://doi.org/10.1016/j.ejpn.2016.07.007

Jacobacci, F., Armony, J. L., Yeffal, A., Lerner, G., Amaro, E., Jovicich, J., Doyon, J., & Della-Maggiore, V. (2020). Rapid hippocampal plasticity supports motor sequence learning. *Proceedings of the National Academy of Sciences*, *117*(38), 23898–23903. https://doi.org/10.1073/pnas.2009576117

Janacsek, K., Fiser, J., & Nemeth, D. (2012). The best time to acquire new skills: Age-related differences in implicit sequence learning across the human lifespan. *Developmental Science*, *15*(4), Article 4. https://doi.org/10.1111/j.1467-7687.2012.01150.x

King, B. R., Hoedlmoser, K., Hirschauer, F., Dolfen, N., & Albouy, G. (2017). Sleeping on the motor engram: The multifaceted nature of sleep-related motor memory consolidation. *Neuroscience & Biobehavioral Reviews*, *80*, 1–22. https://doi.org/10.1016/j.neubiorev.2017.04.026

King, B. R., Saucier, P., Albouy, G., Fogel, S. M., Rumpf, J.-J., Klann, J., Buccino, G., Binkofski, F., Classen, J., Karni, A., & Doyon, J. (2016). Cerebral Activation During Initial Motor Learning Forecasts Subsequent Sleep-Facilitated Memory Consolidation in Older Adults. *Cerebral Cortex*, bhv347. https://doi.org/10.1093/cercor/bhv347

Kleiner, M., Brainard, D., Pelli, D., Broussard, C., Wolf, T., & Niehorster, D. (2006). *Psychtoolbox-3* (Version 3) [Computer software]. http://psychtoolbox.org/

Krakauer, J. W., Hadjiosif, A. M., Xu, J., Wong, A. L., & Haith, A. M. (2019). Motor Learning. In R. Terjung (Ed.), *Comprehensive Physiology* (1st ed., pp. 613–663). Wiley. https://doi.org/10.1002/cphy.c170043

Kwon, D., Pfefferbaum, A., Sullivan, E. V., & Pohl, K. M. (2020). Regional growth trajectories of cortical myelination in adolescents and young adults: Longitudinal validation and functional correlates. *Brain Imaging and Behavior*, *14*(1), 242–266. https://doi.org/10.1007/s11682-018-9980-3

Leversen, J. S. R., Haga, M., & Sigmundsson, H. (2012). From Children to Adults: Motor Performance across the Life-Span. *PLoS ONE*, *7*(6), e38830. https://doi.org/10.1371/journal.pone.0038830

Loh, S., Lamond, N., Dorrian, J., Roach, G., & Dawson, D. (2004). The validity of psychomotor vigilance tasks of less than 10-minute duration. *Behavior Research Methods, Instruments, & Computers*, *36*(2), 339–346. https://doi.org/10.3758/BF03195580

Maclean, A. W., Fekken, G. C., Saskin, P., & Knowles, J. B. (1992). Psychometric evaluation of the Stanford Sleepiness Scale. *Journal of Sleep Research*, *1*(1), Article 1. https://doi.org/10.1111/j.1365-2869.1992.tb00006.x

Meulemans, T., Van der Linden, M., & Perruchet, P. (1998). Implicit sequence learning in children. *Journal of Experimental Child Psychology*, *69*(3), Article 3. https://doi.org/10.1006/jecp.1998.2442

Morita, T., Asada, M., & Naito, E. (2019). Developmental Changes in Task-Induced Brain Deactivation in Humans Revealed by a Motor Task. *Developmental Neurobiology*, *79*(6), 536–558. https://doi.org/10.1002/dneu.22701

Mostofsky, S. H., Rimrodt, S. L., Schafer, J. G. B., Boyce, A., Goldberg, M. C., Pekar, J. J., & Denckla, M. B. (2006). Atypical Motor and Sensory Cortex Activation in Attention-Deficit/Hyperactivity Disorder: A Functional Magnetic Resonance Imaging Study of Simple Sequential Finger Tapping. *Biological Psychiatry*, *59*(1), 48–56. https://doi.org/10.1016/j.biopsych.2005.06.011

Muftuler, L. T., Davis, E. P., Buss, C., Head, K., Hasso, A. N., & Sandman, C. A. (2011). Cortical and subcortical changes in typically developing preadolescent children. *Brain Research*, *1399*, 15–24. https://doi.org/10.1016/j.brainres.2011.05.018

Nicolas, J., King, B. R., Lévesque, D., Lazzouni, L., Leroux, G., Wang, D., Grossman, N., Swinnen, S. P., Doyon, J., Carrier, J., & Albouy, G. (2025). Unraveling the neurophysiological correlates of phase-specific enhancement of motor memory

consolidation via slow-wave closed-loop targeted memory reactivation. *Nature Communications*, *16*(1), 2644. https://doi.org/10.1038/s41467-025-57602-2

Ohayon, M. M., Carskadon, M. A., Guilleminault, C., & Vitiello, M. V. (2004). Meta-Analysis of Quantitative Sleep Parameters From Childhood to Old Age in Healthy Individuals: Developing Normative Sleep Values Across the Human Lifespan. *Sleep*, *27*(7), Article 7. https://doi.org/10.1093/sleep/27.7.1255

Olesen, P. J., Nagy, Z., Westerberg, H., & Klingberg, T. (2003). Combined analysis of DTI and fMRI data reveals a joint maturation of white and grey matter in a fronto-parietal network. *Cognitive Brain Research*, *18*(1), 48–57. https://doi.org/10.1016/j.cogbrainres.2003.09.003

Østby, Y., Tamnes, C. K., Fjell, A. M., Westlye, L. T., Due-Tønnessen, P., & Walhovd, K. B. (2009). Heterogeneity in Subcortical Brain Development: A Structural Magnetic Resonance Imaging Study of Brain Maturation from 8 to 30 Years. *The Journal of Neuroscience*, *29*(38), 11772–11782. https://doi.org/10.1523/JNEUROSCI.1242-09.2009

Pan, S. C., & Rickard, T. C. (2015a). Sleep and motor learning: Is there room for consolidation? *Psychological Bulletin*, *141*(4), Article 4. https://doi.org/10.1037/bul0000009

Pan, S. C., & Rickard, T. C. (2015b). *Sleep and Motor Learning: Is There Room for Consolidation ? 141*(4), 812–834.

Poldrack, R. A. (2007). Region of interest analysis for fMRI. *Social Cognitive and Affective Neuroscience*, *2*(1), 67–70. https://doi.org/10.1093/scan/nsm006

Poldrack, R. A., Fletcher, P. C., Henson, R. N., Worsley, K. J., Brett, M., & Nichols, T. E. (2008). Guidelines for reporting an fMRI study. *NeuroImage*, *40*(2), 409–414. https://doi.org/10.1016/j.neuroimage.2007.11.048

Raichle, M. E. (2015). The Brain's Default Mode Network. *Annual Review of Neuroscience*, *38*(1), 433–447. https://doi.org/10.1146/annurev-neuro-071013-014030

Reverberi, S., Dolfen, N., Van Roy, A., Albouy, G., & King, B. R. (2023). Sleep does not influence schema-facilitated motor memory consolidation. *PLOS ONE*, *18*(1), Article 1. https://doi.org/10.1371/journal.pone.0280591

Robertson, E. M., Press, D. Z., & Pascual-Leone, A. (2005). Off-Line Learning and the Primary Motor Cortex. *The Journal of Neuroscience*, *25*(27), 6372–6378. https://doi.org/10.1523/JNEUROSCI.1851-05.2005

Rolls, E. T., Huang, C.-C., Lin, C.-P., Feng, J., & Joliot, M. (2020). Automated anatomical labelling atlas 3. *NeuroImage*, *206*, 116189. https://doi.org/10.1016/j.neuroimage.2019.116189

Salehi, S. K., Sheikh, M., Hemayattalab, R., & Humaneyan, D. (2016). The Effect of Different Ages levels and explicit-implicit Knowledge on Motor Sequence Learning. *Internation Journal of Environmental & Science Education*, *11*(18), Article 18.

Sharer, E., Crocetti, D., Muschelli, J., Barber, A. D., Nebel, M. B., Caffo, B. S., Pekar, J. J., & Mostofsky, S. H. (2015). Neural Correlates of Visuomotor Learning in Autism. *Journal of Child Neurology*, *30*(14), 1877–1886. https://doi.org/10.1177/0883073815600869

Sjøgård, M., Baxter, B., Mylonas, D., Thompson, M., Kwok, K., Driscoll, B., Tolosa, A., Shi, W., Stickgold, R., Vangel, M., Chu, C. J., & Manoach, D. S. (2024). *Hippocampal ripples predict motor learning during brief rest breaks in humans*. https://doi.org/10.1101/2024.05.02.592200

Sugawara, S. K., Tanaka, S., Tanaka, D., Seki, A., Uchiyama, H. T., Okazaki, S., Koeda, T., & Sadato, N. (2014). Sleep Is Associated with Offline Improvement of Motor Sequence Skill in Children. *PLoS ONE*, *9*(11), Article 11. https://doi.org/10.1371/journal.pone.0111635

Thomas, K. M., Hunt, R. H., Vizueta, N., Sommer, T., Durston, S., Yang, Y., & Worden, M. S. (2004). Evidence of developmental differences in implicit sequence learning: An fMRI study of children and adults. *Journal of Cognitive Neuroscience*, *16*(8), 1339–1351. https://doi.org/10.1162/0898929042304688

Van Roy, A., Albouy, G., Burns, R. D., & King, B. R. (2024). Children exhibit a developmental advantage in the offline processing of a learned motor sequence. *Communications Psychology*, *2*(1), 30. https://doi.org/10.1038/s44271-024-00082-9

Voisin, D., Peigneux, P., & Urbain, C. (2024). Active and Passive Offline Breaks Differentially Impact the Consolidation of Procedural Motor Memories in Children and Adults. *Brain and Behavior*, *14*(11), e70138. https://doi.org/10.1002/brb3.70138

Walker, M. P., Stickgold, R., Alsop, D., Gaab, N., & Schlaug, G. (2005). Sleep-dependent motor memory plasticity in the human brain. *Neuroscience*, *133*(4), 911–917. https://doi.org/10.1016/j.neuroscience.2005.04.007

Wang, Y., Huynh, A. T., Bao, S., Buchanan, J. J., Wright, D. L., & Lei, Y. (2024). Memory consolidation of sequence learning and dynamic adaptation during wakefulness. *Cerebral Cortex*, bhad507. https://doi.org/10.1093/cercor/bhad507

Wilhelm, I., Diekelmann, S., & Born, J. (2008). Sleep in children improves memory performance on declarative but not procedural tasks. *Learning & Memory*, *15*(5), Article 5. https://doi.org/10.1101/lm.803708