Procedural learning: A developmental study of motor sequence learning and probabilistic classification learning in school-aged children

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**Abstract**

In this study, we investigated motor and cognitive procedural learning in typically developing children aged 8–12 years with a serial reaction time (SRT) task and a probabilistic classification learning (PCL) task. The aims were to replicate and extend the results of previous SRT studies, to investigate PCL in school-aged children, to explore the contribution of declarative knowledge to SRT and PCL performance, to explore the strategies used by children in the PCL task via a mathematical model, and to see whether performances obtained in motor and cognitive tasks correlated. The results showed similar learning effects in the three age groups in the SRT and in the first half of the PCL tasks. Participants did not develop explicit knowledge in the SRT task whereas declarative knowledge of the cue–outcome associations correlated with the performances in the second half of the PCL task, suggesting a participation of explicit knowledge after some time of exposure in PCL. An increasing proportion of the optimal strategy use with increasing age was observed in the PCL task. Finally, no correlation appeared between cognitive [...]
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Procedural learning: A developmental study of motor sequence learning and probabilistic classification learning in school-aged children

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In this study, we investigated motor and cognitive procedural learning in typically developing children aged 8–12 years with a serial reaction time (SRT) task and a probabilistic classification learning (PCL) task. The aims were to replicate and extend the results of previous SRT studies, to investigate PCL in school-aged children, to explore the contribution of declarative knowledge to SRT and PCL performance, to explore the strategies used by children in the PCL task via a mathematical model, and to see whether performances obtained in motor and cognitive tasks correlated. The results showed similar learning effects in the three age groups in the SRT and in the first half of the PCL tasks. Participants did not develop explicit knowledge in the SRT task whereas declarative knowledge of the cue–outcome associations correlated with the performances in the second half of the PCL task, suggesting a participation of explicit knowledge after some time of exposure in PCL. An increasing proportion of the optimal strategy use with increasing age was observed in the PCL task. Finally, no correlation appeared between cognitive and motor performance. In conclusion, we extended the hypothesis of age invariance from motor to cognitive procedural learning, which had not been done previously. The ability to adopt more efficient learning strategies with age may rely on the maturation of the fronto-striatal loops. The lack of correlation between performance in the SRT task and the first part of the PCL task suggests dissociable developmental trajectories within the procedural memory system.

Keywords: Procedural learning; Serial reaction time task; Probabilistic classification learning task; Motor procedural learning; Cognitive procedural learning; Child development.

Procedural learning belongs to the non-declarative or implicit learning system and refers to the ability to learn complex information without awareness. It consists in a progressive improvement of skills, without explicit knowledge or voluntary recall. Unlike declarative

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or explicit memory, which becomes more and more powerful from childhood to adulthood (Bauer, 1996; Bauer & Mandler, 1989; Newcombe, Lloyd, & Ratliff, 2007; Van der Linden, 2009), procedural learning is already well developed in infants (DiGiulio, Seidenberg, O’Leary, & Raz, 1994; Parkin, 1997). Babies as young as three months old are actually able to learn visual sequences (Haith & McCarty, 1990; Smith, Loboschefski, Davidson, & Dixon, 1997) and eight-month-old infants can detect sequence regularities after a short exposure to an artificial language (Aslin, Saffran, & Newport, 1998). These findings suggest that procedural memory is a phylogenetically and ontogenetically more primitive system than declarative memory (Nelson, 1997). Procedural learning plays an important role in the child’s early acquisitions, and deficits in this domain are thought to be at the origin of neurodevelopmental disorders such as specific language impairment (SLI) and developmental coordination disorder (DCD). Whereas many studies now explore the hypothesis of a link between impaired language or motor development and procedural learning deficits by studying clinical populations (Gabriel et al., 2013; Gabriel, Maillart, Guillaume, Stefaniak, & Meulemans, 2011; Gabriel, Stefaniak, Maillart, Schmitz, & Meulemans, 2012; Gheysen, Van Waelvelde, & Fias, 2011; Hedenius et al., 2011; Kémeny & Lukács, 2010; Lejeune, Catala, Willems, & Meulemans, 2013; Lum & Blese, 2012; Lum, Conti-Ramsden, Morgan, & Ullman, 2014; Lum, Conti-Ramsden, Page, & Ullman, 2011; Lum, Gelgic, & Conti-Ramsden, 2010; Mayor-Dubois, Van der Linden, Zesiger, & Roulet-Perez, 2012; Tomblin, Mainela-Arnold, & Zhang, 2007), it appears necessary to better define procedural learning abilities in typically developing children.

In school-aged children, most studies of procedural learning explore its motor component using serial reaction time (SRT) tasks (e.g., Janacsek, Fiser, & Nemeth, 2012; Karatekin, Marcus, & White, 2007; Meulemans, Van der Linden, & Perruchet, 1998; Nissen & Bullemer, 1987; Savion-Lemieu, Bailey, & Penhune, 2009; Thomas et al., 2004; Thomas & Nelson, 2001; Weierman & Meier, 2012). In this type of task, participants have to respond as quickly as possible to a stimulus appearing in a specific location on a screen by pressing the corresponding key of a keyboard. Faster reaction times (RTs) are observed for reoccurring but not for random sequences of stimuli, the participant being unaware of the repetitive structure of the task. Classical paradigms start with a baseline of random trials (constituting the first block of trials), followed by a fixed, repeating sequence of positions which is presented iteratively for several blocks of trials and finally end with again a block of random trials (for example, one block of random trials, five blocks of repeating sequences, and one block of random trials). In order to avoid the participation of declarative knowledge of the sequence, Meulemans et al. (1998) created a paradigm in which the repeating sequence of stimuli alternate with series of random stimuli. They investigated motor learning in children aged 6 and 10 years and in adults, and found that motor learning—measured by the decrease of RTs for the repeating sequence—was identical for the three age groups. The SRT task was followed by a recognition task in which the participants were asked to identify the sequence presented in the learning session among novel never presented sequences. Scores were at chance in all age groups, indicating that participants had no explicit knowledge of the sequence.

Whereas Meulemans et al. (1998) found no differences in the magnitude of motor learning across childhood to adulthood (Karatekin et al., 2007; Meulemans et al., 1998), other studies either showed that older children (aged 10–16 years) and young adults outperformed younger children aged 4–7 years (Savion-Lemieu et al., 2009; Thomas et al., 2004; Thomas & Nelson, 2001; Weierman & Meier, 2012) or found that motor
learning was more efficient in childhood than in adolescence and adulthood (Janacsek et al., 2012). These contradictory findings challenge the issue of age invariance in procedural motor sequence learning. Methodological differences (e.g., classical versus alternating sequences paradigm, length and complexity of the sequences used, probabilistic structure of the design) may explain the differences in the results obtained. In addition, recruitment/participation of declarative memory may be responsible for enhanced performance in motor sequence learning tasks in older compared to younger children (e.g., Janacsek et al., 2012; Thomas et al., 2004; Thomas & Nelson, 2001; Weierman & Meier, 2012).

Whereas procedural learning was initially thought to mainly support motor learning, it progressively appeared to also support associative cognitive learning, also called “habit learning” by some authors (Graybiel, 2008; Knowlton & Moody, 2008; Packard & Knowlton, 2002). A typical cognitive learning paradigm is the probabilistic classification learning (PCL) task, originally named the “weather prediction task” (Knowlton, Mangels, & Squire, 1996); in this task, participants have to predict the outcome (rain or sunshine) out of a combination of several cues (sets of cards) and gradually learn the associations between cues and outcome via feedback. Gluck, Shohamy, and Myers (2002) showed that healthy young adults used different types of associative learning strategies, ranging from an optimal multicue integrative learning strategy to suboptimal single-cue learning strategies. Interestingly, Gluck et al. reported that there was no relation between the learning strategy the participants actually applied during the classification learning phase and the strategy they thought they had used when asked afterwards, suggesting that the type of associative learning used during the PCL task cannot be consciously recollected.

Motor sequence learning and probabilistic classification learning have been shown to be supported by fronto-striatal networks. They have first been largely studied in clinical settings with adults presenting with neurological disorders involving basal ganglia, via SRT tasks (Corkin, 1968; Damasio, Eslinger, Damasio, Van Hoesen, & Cornell, 1985; Jackson, Jackson, Harrison, Henderson, & Kennard, 1995; Milner, 1962; Muslimovic, Post, Speelman, & Schmand, 2007; Stefanova, Kostic, Zirodaj, Markovic, & Ocić, 2000) and via PCL tasks (Eldridge, Masterman, & Knowlton, 2002; Knowlton, Mangels, & Squire, 1996; Knowlton, Squire, & Gluck, 1994; Knowlton, Squire, Paulsen, Swerdlow, & Swenson, 1996). More recently, functional neuroimaging studies with healthy adults performing an SRT task have shown activations in the right caudate and right putamen in association with the premotor cortex and supplementary motor area, cerebellum and bilateral parietal regions (Daselaar, Rombouts, Veltman, Raaijmakers, & Jonker, 2003; Grafton, Hazeltine, & Ivry, 1995; Poldrack et al., 2005; Rauch et al., 1997). More detailed analyses revealed that sequence motor learning was predominantly associated with activity in the putamen (Rauch et al., 1997). In the PCL task, healthy subjects showed activation in the right caudate nucleus (Aron et al., 2004; Poldrack, Prabhakaran, Seger, & Gabrieli, 1999; Seger & Cincotta, 2005), as well as in the bilateral frontal cortices and in the occipital cortex. Hence, the putamen appears to be selectively involved in motor learning, and the caudate in cognitive learning.

Children with striatal damage or dysfunction appear to present with similar procedural memory impairments to adults, suggesting that fronto-striatal networks also support motor and cognitive procedural learning in childhood (Mayor-Dubois, Maeder, Zesiger, & Roulet-Perez, 2010). However, it remains important to understand whether the procedural learning system is unitary or composed of various independent dissociable subcomponents (motor versus cognitive learning). Recent clinical studies in adults have provided
arguments in favor of a dissociation between motor and cognitive learning (Foerde et al., 2008; Marsh, Alexander, Packard, Zhu, & Peterson, 2005), but, to our knowledge, no study has investigated this issue in typically developing children.

In this study, we explored the different facets of procedural learning in a cohort of typically developing school-aged children with the hypothesis that the age invariance principle of procedural learning would apply to both the motor and the cognitive domains. Our aims were: (1) to replicate but also to extend to different age groups the data on motor learning with an SRT task; (2) to explore the development of cognitive learning in school-aged children with a PCL task; (3) to assess the possible contribution of declarative memory to procedural learning by adding tests and questionnaires of explicit knowledge at the end of both tasks (as declarative memory, but not procedural learning, is expected to increase in middle childhood, this age period seemed optimal for exploring the interaction of both memory systems); (4) to explore what strategies the children used in the PCL task according to Gluck et al.’s (2002) mathematical model and to investigate if they evolved with age; and (5) to explore the relationship between motor and cognitive learning during development by examining whether the performances in the SRT task and the PCL task correlated.

METHODS

Participants

A total of 72 children distributed across three age groups—8, 10 and 12 years of age—participated in the experiments; there were 24 children aged 8 years, 25 children aged 10 years, and 23 children aged 12 years (Table 1). All children were recruited from the same mainstream school (middle socioeconomic class). They had no learning difficulties, no speech and language therapy and were taking no medication according to their teacher and to a questionnaire filled out by the parents. Written informed parental consent was obtained for each child.

Experimental Tasks

Serial Reaction Time (SRT). We chose and used Meulemans et al.’s (1998) experimental paradigm because the alternating random versus repeating sequences design has been shown to impede the participation of explicit knowledge. Each child sat at a comfortable distance from the computer, and placed his or her middle finger and forefinger of each hand on four keys (the letters X, C, N, M on the Swiss French QWERTZ keyboard). Each child was instructed to respond as quickly as possible to an asterisk appearing in one of four possible positions displayed on the screen by pushing the

Table 1 Demographic data of the participants performing the SRT task and the PCL task.

<table>
<thead>
<tr>
<th></th>
<th>8-year-old group</th>
<th>10-year-old group</th>
<th>12-year-old group</th>
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<tbody>
<tr>
<td>SRT task</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of participants</td>
<td>24 (11 girls)</td>
<td>24 (10 girls)</td>
<td>21 (11 girls)</td>
</tr>
<tr>
<td>Mean age (range)</td>
<td>8y6m (7y10m–8y11m)</td>
<td>10y4m (9y10m–10y10m)</td>
<td>12y6m (11y8m–12y11m)</td>
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<tr>
<td>PCL task</td>
<td></td>
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</tr>
<tr>
<td>Number of participants</td>
<td>24 (13 girls)</td>
<td>25 (13 girls)</td>
<td>23 (12 girls)</td>
</tr>
<tr>
<td>Mean age (range)</td>
<td>8y4m (7y11m–8y9m)</td>
<td>10y4m (9y9m–10y9m)</td>
<td>12y4m (11y8m–12y10m)</td>
</tr>
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corresponding key. Four arrows, indicating the possible locations, remained displayed during the whole session. The next asterisk appeared only once the participant had correctly responded, with a delay of 250 ms. Five blocks of 84 trials were administered (total of 240 trials). In each block, a sequence composed of random trials alternated with a repeated sequence (C-M-X-N-M-C-X-M-N-X) of 10 positions. The positions of the target in the random sequence were determined randomly, except that two asterisks could not appear in the same location consecutively. In addition, in each block, the four locations appeared in the same proportion as in the repeating sequences in order to have an equal distribution (X and M: 30%, C and N: 20%). In this task, we expected a decrease in RT for the repeated sequences but not for the random stimuli as the trials proceeded.

Each block included 84 trials and started with 4 random trials, followed by the presentation of the repeating sequence (10 trials), after which 6 random trials were presented. Because of their unpredictability, the first two stimuli of the repeating sequence were considered in the analysis as belonging to the random sequence. The repeating and random sequences considered for the analysis comprised the same number of stimuli (eight in each).

Learning was measured by computing the median of the RTs for correct responses for both repeating and random sequences in each block. Accuracy was also measured by computing the number of errors for both repeating and random sequences in each block.

**Declarative Knowledge.** A recognition test was administered at the end of the learning phase in order to check whether or not the participant was able to remember some of the sequences. The child had to judge whether or not a given sequence was displayed in the learning test by giving a yes/no answer. A total of 16 sequences of 4 positions were proposed, 8 sequences belonging to the repeating sequence (“known”), and 8 sequences not presented in the learning phase (“new”). The known and new sequences were presented in a random order and we computed the number of correct responses (maximum score = 16 correct responses, chance equals 8).

**Probabilistic Classification Learning (PCL).** We used the paradigm described in Shohamy et al. (2004) designed for adults, and later used with children (Mayor-Dubois et al., 2010). Participants were instructed to predict the flavor of ice cream (vanilla or chocolate) that the presented figure was going to choose. The figure consisted of a basic shape (head with black eyes, red nose, mouth, arms and feet) on which one to three out of four different attributes (cues) were added (hat, sunglasses, moustache, tie), for a total of 14 different figures. Each cue was associated with a flavor (outcome), with a distinct level of probability. Over the whole test, each outcome occurred equally often (50% vanilla, 50% chocolate). The probability of vanilla for the different cues (hat, glasses, moustache, tie) was respectively 0.8, 0.6, 0.4 and 0.2 and the probability of chocolate for these features was correspondingly 0.2, 0.4, 0.6 and 0.8.

The figures were presented one at a time on a computer screen, in a randomized order (but fixed for all subjects). Once the prediction was done, feedback was given (the correct ice cream appears together with the figure presented). If the guess was correct, coins appeared with a corresponding sound of falling coins. In this task, we expected progressive learning of the cue–outcome associations (i.e., increase in correct responses) as the test progressed. The number of correct responses was computed in four blocks of 50 trials over the whole test (200 trials). Following previous PCL studies, the participant’s
response was judged correct if it corresponded to the most probable outcome for that figure (if the probability for this outcome is superior to 0.5).

**Declarative Knowledge.** At the end of the learning phase, an open questionnaire was administered in order to evaluate whether or not the participant had developed explicit knowledge of the cue–outcome associations. The participant was credited points according to the quality of his or her declarative knowledge (i.e., if the participant had detected the cues, and if he or she could mention which cues were associated to which flavor), with a maximum score of 10 points.

**Strategy Analysis.** To investigate the learning strategies, we applied the mathematical model proposed by Gluck et al. (2002). This allows the delineation of response patterns based on how an ideal participant would respond to each trial if he or she had been following one of the three possible strategies, called multicue, one-cue or singleton.

For each child, we calculated the degree to which each ideal mathematical model fitted the participant’s data (0.0 indicating a perfect fit). The best-fit model, i.e., the closest corresponding one to the individual response profile of each participant, was chosen.

Referring to Gluck et al. (2002), we considered the three following strategies. In the **multicue strategy**, the participant responds to each trial on the basis of the most frequent outcome associated with that particular combination of cues. This strategy demands attending to all cues presented on each trial. In the **one-cue strategy**, the participant responds to each trial on the basis of the presence or absence of one particular cue, without considering the other cues. For example, he would respond “vanilla” if the tie is present and “chocolate” otherwise. In the **singleton strategy**, the participant learns the outcome associated with the trials in which only one single cue appears, and responds randomly when the man displays several cues simultaneously.

The analyses of strategies consisted of (1) exploring the type of strategies used by the children across the age groups (8, 10, and 12 years), (2) examining the relationship between the type of strategy and the learning score, (3) investigating the relationship between the strategy and the explicit knowledge of cue association, and (4) testing for correlations between learning scores and explicit knowledge according to the different strategies.

**RESULTS**

Preliminary descriptive data analyses were performed on the scores of the SRT task (median RTs and number of errors) and the PCL task (number of correct responses) per age group and per condition in order to ensure that the data distribution was normal. There were no outliers in the PCL task, and one outlier in the SRT task. This participant (boy, aged 10 years) exhibited very slow RTs compared to his age peers (i.e., > 1800 ms) and his data were therefore removed from further analyses.

**Serial Reaction Time (SRT)**

Figure 1 displays the average median RTs for the random and repeating sequences in each age group. We tested whether motor learning could be documented through the decrease of the RT for the repeated sequences specifically. An analysis of variance (ANOVA) with Age as the between-subject variable (8, 10, and 12 years), and
Sequence type (repeating vs random) and Blocks (1–5) as repeated measures was computed over the median RTs. Results showed that RT did not significantly differ along the Blocks \( F(4, 64) = 2.49, p = .051, \text{partial } \eta^2 = .135 \) but that they differed for each type of Sequence \( F(1, 67) = 34.64, p = .000, \text{partial } \eta^2 = .341 \). A sequence-specific learning

**Figure 1** Performance of 8-, 10-, and 12-year-old children in the SRT task: (A) RTs across all blocks; (B) RTs in both the random and repeated sequences at the end of the learning phase (Block 5).

Note: The RTs improve with age (slowest baseline RTs in 8-year-olds, fastest in 12-year-olds), but the RTs also decrease along the blocks in the youngest age group, indicating an overall improvement of motor efficiency with practice due to motor immaturity, independently from specific sequence learning. Specific and statistically significant motor learning is found for each age group, as shown by the acceleration of the RTs for the repeated sequences (curves in gray) compared to the random sequences (curves in black).
occurred [interaction Sequence × Block: $F(4, 64) = 2.58, p = .045$, partial $\eta^2 = .139$]. Global RTs evolved differentially along the Blocks according to Age [interaction Age × Block: $F(8, 130) = 2.70, p = .009$, partial $\eta^2 = .143$]: RTs decreased only in the youngest group across the five blocks, indicating an overall improvement of motor efficiency with practice due to motor immaturity in this age group. The differences in RT between the repeating and random sequences were similar in all three age groups [no interaction Age × Sequence: $F(2, 67) = 1.68, p = .193$, partial $\eta^2 = .048$] and there was no triple interaction [$F(8, 130) = 0.63, p = .749$, partial $\eta^2 = .037$], indicating that the learning effect was similar across age groups. Complementary analyses were done per age group in order to see when specific sequence learning effects appeared as a function of age (paired-samples tests). Interestingly, the youngest age group (8 years of age) displayed the earliest learning effect, statistically significant from Block 2 [$t(24) = 1.130, p = .270$; B2: $t(24) = 2.639, p = .014$; B3: $t(24) = 2.679, p = .013$; B4: $t(24) = 3.884, p = .001$; B5: $t(24) = 3.121, p = .005$], whereas the older ones (10 and 12 years of age) displayed learning effects at the end of the task only [10 years of age: B1: $t(23) = 1.613, p = .203$; B2: $t(23) = 0.748, p = .462$; B3: $t(23) = 1.151, p = .262$; B4: $t(23) = 2.767, p = .011$; B5: $t(23) = 2.890, p = .008$. 12 years of age: B1: $t(20) = 0.758, p = .457$; B2: $t(20) = 0.515, p = .612$; B3: $t(20) = 4.002, p = .001$; B4: $t(20) = 2.664, p = .015$; B5: $t(2) = 1.631, p = .119$].

Finally we looked at accuracy by computing the number of errors committed by the children. An ANOVA with Age as the between-subject variable (8, 10, and 12 years), and Sequence type (repeating vs random) and Blocks (1–5) as the repeated measures was computed over the number of errors committed during SRT learning. The results showed that the number of errors was significantly different according to the Sequence type [$F(1, 67) = 26.579, p = .000$, partial $\eta^2 = .284$]. There was no interaction between the number of errors and Age [$F(1, 67) = 0.518, p = .598$, partial $\eta^2 = .015$], showing that accuracy did not differ significantly between younger and older children. The number of errors did not differ significantly along the Blocks [$F(1, 67) = 1.534, p = .203$, partial $\eta^2 = .087$], suggesting that the number of errors did not diminish during the learning phase. Lastly, there was no triple interaction (Sequence type × Blocks × Age), suggesting that the number of errors did not evolve in a different way across age groups.

Declarative Knowledge. No declarative knowledge of the repeating sequence was acquired by the participants (maximum of 16 correct responses), the mean score being 7.76 ($SD = 1.8$) for the 8-year-olds, 7.81 ($SD = 1.7$) for the 10-year-olds and 7.19 ($SD = 1.5$) for the 12-year-olds (where chance equals 8). Moreover, declarative knowledge scores did not correlate with SRT learning effect at B5 [$r(70) = 0.036, p = .768$].

Probabilistic Classification Learning (PCL)

In order to track the evolution of cognitive learning throughout the test (Figure 2), we computed an ANOVA with Blocks (4) as the repeated measure and Age (8, 10, and 12 years) as the between-subject variable. The results showed an effect of Blocks, indicating an improvement of performance across the four blocks of 50 trials [$F(3, 67) = 13.15, p = .000$, partial $\eta^2 = .371$]. There was no interaction between Age and Blocks [$F(6, 136) = 1.22, p = .297$, partial $\eta^2 = .051$], indicating similar learning across Blocks in all
Multiple post hoc comparisons indicated that the only significant difference appeared between 8- and 12-year-old children (Tukey: \( p = .013 \)).

In the questionnaire of declarative knowledge about cue–outcome associations, the scores attained in the 8-, 10-, and 12-year-old groups were 5.9, 7, and 7.3 points respectively (out of a maximum of 10 points). The ANOVA showed that the scores differed with age \([F(2, 69) = 3.95, p = .024, \text{partial } \eta^2 = .103]\) and multiple post hoc comparisons indicated significant differences between the 8- and 12-year-old groups only (Tukey, \( p = .028 \)), suggesting poorer explicit knowledge in the youngest age group only.

We further explored the relation between the performance (obtained in the four blocks of 50 trials) and the declarative knowledge of the cue–outcome association with Pearson bivariate correlations. For the whole group (all ages together), correlations appeared highly significant in the second part of the test \([B3: r(72) = .409, p = .000; B4: r(72) = .380, p = .001]\) but not in the first two blocks of the learning phase \([B1: r(72) = .104, p = .385; B2: r(72) = .179, p = .133]\). Analysis per age group showed significant correlations between the declarative knowledge scores and the performances obtained in the last block (B4) for the 10- and 12-year-olds \([\text{respectively } r(25) = .441, p = .027; r(23) = .551, p = .006]\), whereas correlations nearly reached significance for B3 in the 8-year-old group \([r(24) = .402, p = .052]\).

**Strategy Analyses**

*Types of strategies across age groups.* Analysis of the whole test (Figure 3A) showed that the younger children mostly used the singleton strategy, and that the proportion of singleton strategy users progressively decreased with age (83.3%, 64%, and 47.8% at ages 8, 10, and 12 years respectively) in favor of an increase of the multicue strategy (16.6%, 28%, and 43.4% at ages 8, 10, and 12 years respectively). The one-cue strategy appeared to be only marginally used by the 10- and 12-year-olds (around...
Figure 3 Strategy analyses in the PCL task, by age group: (A) Percentage of participants using the multicue, one-cue or singleton strategy, as a function of age; (B) Percentage of correct responses obtained in Blocks 1–4, as a function of the use of the optimal multicue strategy (B1) and non-optimal singleton strategy (B2).

Note: There is a significant increase in the use of the optimal multicue strategy with age. The percentage of correct responses is very similar for all age groups when the children are matched on the type of cognitive strategy used.
8–9% in). Multiple post hoc analyses showed that the type of strategy was significantly different between the 8- and 12-year-olds (Tukey: $p = .049$) but not between the 8- and 10-year-olds (Tukey: $p = .400$) or between the 10- and 12-year-olds (Tukey: $p = .506$).

**Relationship between strategy and learning score.** As a group, participants using a multicue strategy had significantly higher scores all through the test than those using a singleton or one-cue strategy (Figure 3B). Interestingly, the learning scores obtained in the four blocks were similar across all age groups when subjects were matched on the type of strategy used. There was a significant effect of Block [$F(3, 61) = 7.88$, $p = .000$, partial $\eta^2 = .279$] but no Strategy × Block interaction [$F(6, 124) = 1.48$, $p = .391$, partial $\eta^2 = .049$] and no Block × Age interaction [$F(6, 124) = 0.75$, $p = .681$, partial $\eta^2 = .031$]. No triple interaction was found [Strategy × Block × Age: $F(9, 189) = 0.376$, $p = .945$, partial $\eta^2 = .018$].

**Correlations between learning score and declarative knowledge according to the different strategy used.** There was no correlation between declarative knowledge and learning scores in participants using the multicue strategy [B1: $r(21) = -.183$, $p = .426$; B2: $r(21) = .06$, $p = .796$; B3: $r(21) = -.03$, $p = .990$; B4: $r(21) = .36$, $p = .109$], indicating that when using an optimal learning strategy, explicit knowledge did not account for learning performance. Correlation between declarative knowledge and learning scores appeared only in the third block for participants using a singleton strategy [B3: $r(46) = .4$, $p = .006$; B1: $r(46) = -.14$, $p = .354$; B2: $r(46) = -.063$, $p = .679$; B4: $r(46) = .238$, $p = .112$].

**Correlations between motor and cognitive learning.** In order to determine whether or not procedural learning develops together or independently in the motor and cognitive domains, we compared the learning gains in both tasks by computing the percentage of gain at the end of the motor task (last block of trials), and in the cognitive task (first half and second half).

For the SRT task, we computed the difference in RT between the random and the repeating sequences of stimuli, by applying the formula $(A_5 - R_5) / A_5 \times 100$, where $A$ represents the mean of the median RT of random stimuli and $R$ represents the mean of the median RT of the repeated sequence, and 5 represents the number of the block taken into account.

For the PCL task, we measured the learning gain in the two different parts of the test, i.e., in the first half of the test (first 100 trials) with the formula $(B_{100} - B_{25}) / B_{25} \times 100$ where $B_{100}$ represents trials 76–100 and $B_{25}$ represents trials 1–25, and in the second half of the test with the formula $(B_{200} - B_{125}) / B_{125} \times 100$, where $B_{200}$ represents trials 176–200 and $B_{125}$ represents trials 101–125. We chose to separate the learning gains obtained in the first and second parts of the PCL, as procedural learning seems to account for performance in the first part of the test whereas declarative learning appears to contribute to performance in the second half of the test.

Correlations between Block 5 of the SRT task and the initial and final parts of the PCL task were then computed. No significant correlation appeared between both tasks either with the data of the whole group of children [B5 & PCLinitial: $r(65) = .029$, $p = .821$; B5 & PCLfinal: $r(65) = -.058$, $p = .646$] or with the data of each age group [8-year-olds: B5 & PCLinitial: $r(23) = .119$, $p = .589$; B5 & PCLfinal: $r(23) = -.117$, $p = .596$; 10-year-olds: B5 & PCLinitial: $r(23) = -.023$, $p = .918$; B5 & PCLfinal: ...
DISCUSSION

In the first part of this study, we showed that 8-, 10-, and 12-year-old children displayed motor procedural learning as measured by RTs, that the performances of the three age groups did not statistically differ from each other and that the participants did not develop explicit knowledge of the sequences. Our results replicate and extend to other age groups those of Meulemans et al. (1998), who tested both children (6- and 10-year-olds) and adults with the same paradigm; comparisons across these two studies suggest that motor learning might not increase across mid-childhood (from 6 to 12 years of age), and may be as efficient as in adults. Complementary analysis per age group showed however that specific sequence learning effects appeared earlier in our youngest age group, as though younger children were more sensitive to sequence detection and learning than older ones. Interestingly, Janacsek et al. (2012) also reported stronger probabilistic sequence learning in children compared to adolescents and adults. Since the declarative memory system is less developed in young children than in older ones (Cycowicz, Friedman, Snodgrass, & Duff, 2001; Drummey & Newcombe, 1995), the former may primarily rely on effective procedural learning only and not try to use a potentially competing less performing declarative learning system, thus allowing for more efficient sequence detection and learning in younger than in older children. As our cohort was small (20–25 participants per age groups) this should be replicated with larger numbers of children. Finally, regarding the accuracy measures, we found that the number of errors was significantly different according to the type of sequences (random versus repeated) but that no specific sequence learning was observed as measured by accuracy in our study. This suggests that RTs and errors may rely on different cognitive underlying processes, also as reported by Janacsek et al. (2012).

In the second part of our study, we showed that 8-year-old children are already able to learn cue–outcome associations in a PCL task. However, while 8-, 10-, and 12-year-old children display similar cognitive learning in the first half of the test (trials 1–100), the older children achieved higher scores in the second part (trials 101–200) even if statistical analysis failed to show a significant effect of age in PCL across the blocks (no Block × Age interaction). We found that declarative knowledge of the cue–outcome association correlated with performances in this second half of the test, indicating a possible contribution of declarative learning after some time of exposure and suggesting that participants try to figure out and remember which cue is associated with which flavor. This is unlikely to happen with the SRT task, during which the participant focuses on execution speed and is thus less prone to notice regularity, especially when an alternating sequence design is used, such as in this study. The enhancement of the performance in the second part of the PCL task was found to be more important in older children (significant differences between 8- and 12-year-olds), explained by declarative memory becoming more powerful with growing age (Cycowicz et al., 2001; DiGiulio et al., 1994; Drummey & Newcombe, 1995). Our results are congruent with data from the clinical studies of adults: patients with procedural learning deficits due to basal ganglia damage failed the initial part of the PCL task, but were able to learn in the later part, whereas those with
amnesia due to temporal lobe damage showed the reverse pattern (Eldridge et al., 2002; Knowlton et al., 1994; Knowlton, Mangels, & Squire, 1996; Knowlton, Squire, et al., 1996). In addition, functional magnetic resonance imaging studies in healthy adults also showed interactions and even a competition between the temporal lobe and the striatal areas during PCL tasks (Poldrack et al., 1999, 2001).

Regarding the strategies used by the children in the PCL task, we found significant changes with age. From 8 to 12 years, the children increasingly used the more efficient multicue strategy while the use of the less efficient singleton strategy decreased. Surprisingly, the young adults reported by Gluck et al. (2002) preferentially used a singleton strategy, as did our younger children. A methodological bias could explain this difference since the cues used in Gluck et al.’s study were more abstract (cards with geometric shapes) than ours (characters with accessories).

Interestingly, the learning scores of our participants did not differ significantly across the age groups when they were matched on the type of strategy. This means that the 8-year-olds performed as well as the 12-year-olds when they used the same strategy, even in the later part of the test. This finding suggests that the multicue strategy is equally efficient in young and older children and provides further arguments in favor of age invariance in cognitive procedural learning. The more frequent use of the multicue strategy as the children grow older could be explained by the maturation of the fronto-striatal loops, allowing for gradual access to more efficient, integrative processing, as shown in other tasks of cognitive control (Ciesielski, Lesnik, Savoy, Grant, & Ahlfors, 2006; Rubia et al., 2006). One can also wonder if declarative knowledge plays a role, but correlations between declarative knowledge and the performance in PCL disappeared when a complex multicue strategy was used. A correlation however persisted between learning scores and declarative knowledge in the second part of the test when a singleton strategy was used. This suggests that an efficient cognitive procedural learning process makes the contribution of declarative knowledge unnecessary or non-significant.

Finally, we found no correlation between the performance in the SRT task and the first part of the PCL tasks. Whether this is due to distinct procedural learning circuits or methodological issues such as the reliability of our measures or psychometric properties of the tasks remains to be elucidated. Both tasks have in common incremental, progressive learning and require the ability to detect regularities from the material presented and to learn to associate the stimuli. The tasks however differ in the sense that the SRT task requires a sequential spatial computation, while simultaneous items have to be learned in the PCL task. Moreover, in the latter, the participant has to learn to predict upcoming outcomes from cues (and thus to make choices), and to categorize the stimuli through feedback-based associative learning. Thus, since learning mechanisms differ, the underlying neural networks are also likely to be different. Recent clinical studies also showed dissociations between preserved motor and impaired cognitive learning in adults with neuropsychiatric disorders (Foerde et al., 2008; Marsh et al., 2005). Conversely, spared cognitive learning but deficient motor learning was observed in two children with progressive idiopathic dystonia (Mayor-Dubois et al., 2010). All these data are in favor of parallel and partially independent networks supporting different types of procedural learning (Alexander, DeLong, & Strick, 1986; Lehericy et al., 2004).

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