Distinct discrimination learning strategies and their relation with spatial memory and attentional control in 4- to 14-year-olds

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Abstract

Behavioral, psychophysiological, and neuropsychological studies have revealed large developmental differences in various learning paradigms where learning from positive and negative feedback is essential. The differences are possibly due to the use of distinct strategies that may be related to spatial working memory and attentional control. In this study, strategies in performing a discrimination learning task were distinguished in a cross-sectional sample of 302 children from 4 to 14 years of age. The trial-by-trial accuracy data were analyzed with mathematical learning models. The best-fitting model revealed three learning strategies: hypothesis testing, slow abrupt learning, and nonlearning. The proportion of hypothesis-testing children increased with age. Nonlearners were present only in the youngest age group. Feature preferences for the irrelevant dimension had a detrimental effect on performance in the youngest age group. The executive functions spatial working memory and attentional control significantly predicted posterior learning strategy probabilities after controlling for age.

Introduction

The ability to learn from feedback is crucial in a changing environment. Using various paradigms in which learning from positive and negative feedback is essential, behavioral, psychophysiological, and neuropsychological studies have revealed large developmental differences in performance. Tasks used in these paradigms include a rule search and application task (van Duijvenvoorde, Zanolie, Rombouts, 2006).
Raijmakers, & Crone, 2008; Zanolie et al., 2008), a rule switch task (Crone, Zanolie, van Leijenhorst, Westenberg, & Rombouts, 2008), the Wisconsin Card Sorting Test (WCST) (Heaton, Chelune, Talley, Kay, & Curtis, 1993), and the discrimination learning task (e.g., Block, Erickson, & McHoes, 1973; Kendler, 1979; Raijmakers, Dolan, & Molenaar, 2001). These tasks have in common that one or more underlying rules need to be inferred from feedback and that the correct solution may be found by testing hypotheses. The results of the studies mentioned above suggest the presence of distinct modes of learning and feedback processing.

In the current study, we used mathematical learning models to distinguish different learning modes on a discrimination learning task and to identify underlying strategies. Our specific aim was to examine the relation between these modes and the executive functions working memory and attentional control. In addition, we investigated the effect of preferences for stimulus features on learning performance.

All of the experimental rule learning tasks mentioned above can be solved by applying hypothesis testing strategies. The tasks differ, inter alia, in the size of the set of possible rules, the number of rule shifts, the presence of ambiguous feedback, and whether the set of possible rules is known to the participants. For instance, on the WCST, a series of unidimensional card sorting rules need to be inferred (from feedback) and applied. Children typically perform worse than adults on a number of measures on the WCST, including the number of perseverative errors (Chelune & Baer, 1986; Heaton et al., 1993; Huizinga, Dolan, & van der Molen, 2006).

In a discrimination learning task, a simple, unidimensional categorization rule needs to be learned from positive and negative feedback (e.g., Kendler, 1979). The set of rules is not explicitly mentioned. In developmental studies using discrimination learning tasks, two distinct modes of learning have been observed—a fast and a slow learning mode—with an age-related increase in the probability of using the fast mode (e.g., Kendler, 1979; Raijmakers et al., 2001). In her levels-of-functioning theory, Kendler (1979) posited that learning in the slow mode is incremental (based on associative stimulus–response learning), whereas the fast mode is based on a hypothesis testing strategy. However, the support for this theory is ambiguous (see Esposito, 1975, for a review). There is some evidence supporting the interpretation of the fast mode as a strategy of efficient hypothesis testing (e.g., Block et al., 1973; Kendler, 1979; Raijmakers et al., 2001). The interpretation of the slow mode in terms of a well-defined strategy is more difficult. A trial-by-trial analysis of discrimination learning performance revealed that learning in the slow mode was abrupt, not incremental (Schmittmann, Visser, & Raijmakers, 2006). This result suggests that learning in the slow mode originated in inefficient hypothesis testing. More specific, Schmittmann and colleagues (2006) hypothesized that the inefficiency in learning is due to inefficient feedback processing in combination with inefficient hypothesis selection due to preferences for the irrelevant dimension. Berkeljon and Raijmakers (2007) investigated this hypothesis in a neural network model of the development of discrimination learning. The combination of a weaker influence of negative feedback (and, therefore, a relatively higher impact of positive feedback) and variability of the initial dimension preference resulted in two modes of output that resembled fast and slow abrupt learning.

To further understand possible hypothesis testing strategies of children, it is useful to consider the following substrategies of efficient hypothesis testing (e.g., Dehaene & Changeux, 1991). A child using the win–stay substrategy randomly samples a rule from a set of rules and applies the rule until an error occurs. In addition, a child can use the lose–shift substrategy, meaning that a different rule is selected from the set of rules once an error is encountered. It is assumed that the new rule is sampled at random from the set.

Studies of the hypothesis testing behavior of children suggest that young children might not apply the strict win–stay and lose–shift substrategies (Gholson, Levine, & Phillips, 1972; Kendler, 1978; Phillips & Levine, 1975). However, these studies arrived at different conclusions, specifically concerning the use of the lose–shift substrategy in the age range of 4 to 10.5 years. This may be due in part to two indeterminacies. First, even if we observe lose–shift behavior on a given trial, we cannot conclude right away that a child actually applies a lose–shift substrategy. For instance, a child may forget to discard a falsified rule, so that the same rule may be sampled again on the subsequent trial, which is a lose–sample substrategy, or a child may use response stereotypes, which refer to position or stimulus feature-based responding that is insensitive to feedback (e.g., consistently choosing the left stimulus;
In the current study, we used mathematical modeling of the complete trial-by-trial data to distinguish between the underlying (e.g., lose–shift, lose–sample) substrategies.

The second indeterminacy originates in the fact that children who choose the correct stimulus due to a marked preference for the correct feature do not need to process negative feedback, that is, apply a lose–shift or lose–sample substrategy. In this case, a win–stay substrategy is sufficient to reach the learning criterion quickly. Indeed, a win–stay strategy is not even necessary because a child with a marked preference can master the task simply by choosing the stimulus with the preferred feature, ignoring feedback altogether. Therefore, we have no means of knowing which substrategy a child who did not receive negative feedback actually applied. To solve this indeterminacy, we modified the task as described in detail below. Our modified task assesses feature preferences and forces all children who show a preference for a feature to learn a feature of their unpreferred dimension. Children without a preference may coincidentally start with the correct feature and should apply a win–stay substrategy to master the task. All remaining children should apply win–stay and lose–shift or lose–sample substrategies to master the task. The modification enables us to examine whether young children use efficient hypothesis testing strategies in discrimination learning. In addition, we can compare the learning processes of children who have a preference for a particular feature with the learning processes of children who have no such preference. Having a preference for an irrelevant feature might hinder the learning process if this preference is resistant or insensitive to negative feedback (Kemler, 1978).

A successful application of the win–stay and lose–shift substrategies requires working memory, attentional control, and cognitive flexibility, which are discussed in the following. Insufficient working memory resources, resulting in a failure to update and keep in mind the set of previously falsified hypotheses and to memorize the current hypothesis, may account for slow discrimination learning. When adults perform a distracter task with a high working memory load simultaneously with a discrimination learning task, their learning efficiency approaches that of children (in terms of the number of trials required to master the discrimination learning task; Sirois & Shultz, 1998). The possible role of working memory is supported by the finding that the dorsolateral prefrontal cortex and superior parietal cortex are involved in both feedback sensitivity (van Duijvenvoorde et al., 2008) and visuospatial working memory task performance (Klingberg, Forssberg, & Westerberg, 2002). A widely accepted conceptualization of working memory includes a supervisory system (the central executive), a phonologically based temporal storage system, and a visuospatially based temporal storage system (Baddeley, 1992). Many working memory tasks, which are designed to measure working memory capacity in specific domains, are available. For example, tasks may require participants to update and manipulate verbal, numerical, spatial, and/or object information. In addition, tasks may vary in whether a repeated replacement of memory content or an accumulation of memory content is required.

Besides working memory limitations, insufficient attentional control may contribute to slow discrimination learning. A successful learner needs to focus his or her attention on relevant stimulus information and to inhibit responses that are based on irrelevant stimulus information. Tasks such as the Stroop task (Stroop, 1935) and flanker task, in which participants are required to respond to the direction of a central arrow that is flanked by congruent or incongruent arrows (e.g., Fan, McCandliss, Sommer, Raz, & Posner, 2002; Ridderinkhof & van der Molen, 1995), are thought to tax this ability.

Cognitive flexibility seems to be particularly important to perform shifts between different hypotheses or dimensions in applying the lose–shift substrategy in discrimination learning (Ashby & O’Brien, 2005). The development of cognitive flexibility has been studied widely in a rule-following and rule-switching paradigm, based on the Dimensional Change Card Sort (DCCS) task (Zelazo, 2006) and DCCS modifications, which are appropriate for older children (e.g., Cepeda & Munakata, 2007; Deák, 2003; Diamond & Kirkham, 2005). Studies based on the DCCS in its standard form show that a large proportion of children from 3 to 5 years of age are able to follow a sorting rule when informed of the rule. However, they perseverate on a rule that they sorted on previously when they are asked to switch to a rule that is based on a conflicting stimulus dimension (Zelazo et al., 2003). Different theoretical frameworks have been proposed to explain perseverative behavior on the DCCS task. According to the attentional inertia theory, children fail to suppress attention to the first dimension, such that they cannot shift attention to the second dimension (Kirkham, Cruess, & Diamond, 2003). In this theory, perseverating children fail to inhibit the prepotent responses that are associated with attention to
the first (now irrelevant) dimension. Alternative explanations concern the ability to formulate higher order rules (cognitive complexity and control theory; Zelazo & Frye, 1997) and the relative strength of active memory (competing memory representations theory; Morton & Munakata, 2002). As mentioned above, our adapted discrimination learning task requires all children who show a preference for a feature to learn a feature of their unpreferred dimension and apply lose-shift or lose-sample behavior. An inability to do so leads to stereotypical responding or perseveration.

The results reviewed above suggest the existence of different strategies of learning. However, the prevalence of the strategies in different age groups is unclear. In the current study, we addressed the development of different strategies in discrimination learning in 4- to 14-year-olds and examined whether strategy use was related to spatial working memory and attentional control. In addition, we investigated the effect of preferences for stimulus features on the learning performance. We hypothesized that young children who have a preference would have more difficulty in learning a feature of the unpreferred dimension than young children who have no such preference. With an increasing ability to switch between dimensions in older children, we expected this effect to wane with age.

**Method**

**Sample**

The participants in the current study were 152 boys and 150 girls in five age groups: 4 and 5 years ($M = 4.91$ years, $SD = 0.54$, $n = 61$, Age Group 1), 6 and 7 years ($M = 7.04$ years, $SD = 0.49$, $n = 50$, Age Group 2), 8 and 9 years ($M = 8.99$ years, $SD = 0.61$, $n = 50$, Age Group 3), 10 to 12 years ($M = 11.58$ years, $SD = 0.89$, $n = 72$, Age Group 4), and 13 and 14 years ($M = 13.94$ years, $SD = 0.53$, $n = 69$, Age Group 5). An additional 6 participants (2 boys and 4 girls) were excluded because they scored lower than 75% correct on a simple two-choice reaction time task. Children were recruited from regular local schools in The Netherlands. With the help of the teachers, children with general health problems or neurological or psychiatric issues were identified and excluded. All participants had normal or corrected-to-normal vision. All participants received a small gift for their participation, and the schools received a book voucher. The sex distribution across the five age groups did not differ significantly, $\chi^2(4) = 2.597$, $p = .627$. Informed consent was obtained in all cases.

**Experimental tasks**

**Discrimination learning**

We used a computerized version of a two-choice discrimination learning task in which a rule-based category structure needed to be learned. The stimuli differed on two binary dimensions: size (large or small) and shape (triangle or circle). Stimuli were presented in pairs of two on a computer screen. Only the four pairings that differed on both dimensions were presented: large triangle–small circle, large circle–small triangle, small triangle–large circle, and small circle–large triangle. One dimension was relevant, and one of the features of the relevant dimension was associated with positive feedback. The other feature of the relevant dimension was associated with negative feedback, and the two features of the irrelevant dimension were paired with the correct feature equally often. The stimulus pairs were randomized in groups of four. The participants were instructed to choose either the left or right stimulus and to make as many correct choices as possible. The stimulus dimensions were not mentioned explicitly. Immediately following a response, feedback appeared below the chosen stimulus in the form of either a cross (negative) or a smile (positive). This feedback remained on the screen for 2000 ms. Following this, the screen went blank and the next trial started.

Prior to this learning block, participants received a fixed set of 6 trials on which they were asked to choose stimuli according to their preference. This preference block served the two purposes of (a) determining whether a participant had a feature preference and (b) assigning all participants with a preference to learn an unpreferred feature. If a participant responded consistently on at least 5 of the 6 trials with one of the four features, the nonpreferred dimension was assigned as the relevant dimension in the learning block. For instance, if a participant chose the triangle on the first 5 trials,
the correct feature in the learning block would be either small or large based on random assignment. If a participant did not respond consistently, the correct feature was chosen at random from all four possible features. Immediately after the last trial of the preference block, the learning block began and continued until a maximum of 48 trials was reached but was terminated earlier if the participant fulfilled the learning criterion. This criterion was predefined as 9 correct responses out of 10 consecutive trials in which the first 3 trials were correct (i.e., 3 correct responses followed immediately by at least 6 correct responses in the next 7 trials). Participants’ responses, including their response times, were recorded on each trial. Before the task started, participants practiced choosing the left or right stimulus by pressing the left or right mouse button with their left or right index finger during practice trials that involved unrelated stimuli (pictures of a bird and a fish).

Working memory
To assess working memory capacity, we chose a spatial working memory task (adapted version of van Leijenhorst, Crone, & van der Molen, 2007) in order to avoid confounds due to age-related changes in verbal and numerical abilities that play a role in the majority of other working memory tasks. In the experimental condition, participants were repeatedly required to update and retrieve information about positions in an array. Whenever a cue appeared in a position, participants could either visit this position or not by pressing one of two response keys (Z or /). Participants were instructed to visit each position in an array exactly once. A block of practice trials with an array of length 5 and one block of test trials (arrays were of lengths 4, 6, and 8) were presented. Participants were instructed to respond as accurately as possible. No time limit was imposed. (For further details on the task, see van Leijenhorst et al., 2007.)

Attentional control
Attentional control was measured with an Eriksen flanker task (adapted from Ridderinkhof & van der Molen, 1995) in which participants were required to respond to a left- or right-pointing arrow presented at the center of the screen by pressing a left or right response key (Z or /). The arrow was flanked by two arrows on each side that pointed either in the same direction (i.e., →→→→→→ or ←←←←←←; congruent condition) or in the opposite direction (i.e., →→→→→→ or ←←←←←←; incongruent condition). Congruent and incongruent trials were presented in a pseudo-random order. The arrows were presented in a rectangle, where the time interval between the onset of the rectangle and the onset of the arrows was 500 ms. Both remained visible until a response was given. The interval between the response and the presentation of the rectangle was 1000 ms. Participants had a maximum of 3000 ms to respond and were instructed to respond as accurately and fast as possible.

Results
In this section, we first present the results that are based on the trial-by-trial analyses of the discrimination learning data. These analyses are based on mathematical modeling of the learning data. After discussing this statistical approach and the mathematical learning models, we present the results in terms of the observed learning strategies and their occurrence in different age groups and at the individual level. Then we turn to lose–shift behavior and stereotypical responding within the learning strategies and the effect of feature preferences on strategy use. After that, we present the results obtained with the executive functioning tasks (i.e., working memory and attentional control) and, finally, the results of the analysis of the relation between learning and executive functioning.

Learning task
Statistical approach
We investigated the number of different learning strategies and the characteristics of these learning strategies by fitting several mathematical learning models that incorporate different hypotheses. The models were fit to the trial-by-trial accuracy data of the 302 participants. The relative fit of the models was compared, and the optimal (best-fitting and most parsimonious) model was selected. Each learning strategy was formalized as a latent Markov model (see Wickens, 1982, for an overview).
In these models, it is assumed that a child can be in one of a discrete number of states during the learning process. For instance, a child may start in a presolution state in which a correct response is made at chance level. On a given trial, the child may switch definitively to a learned state in which the response accuracy is expected to approximate 1. In the models, the following parameters were estimated or fixed to chosen values: the conditional probabilities of a correct response given a state, the transition probabilities between the states (e.g., the probability of a transition from the presolution state to the learned state, i.e., the learning parameter), and the initial probabilities of starting in each state on the first trial. Note that the transition probabilities and the conditional probabilities of a correct response given a state are constant over trials. Different assumptions about the learning processes (e.g., one-trial memory) are formalized in different component models. To accommodate multiple latent strategies in the sample, these models were specified as components in mixture models (e.g., van de Pol & Langeheine, 1990) and the mixing proportions of the components were estimated in addition to the parameters in the component models. In the next section, we describe the single-component models on a conceptual level (see Visser, Schmittmann, & Raijmakers, 2007, for a more technical account).

Learning strategy models

To model hypothesis testing strategies, we fit different models to the data. First, the hypothesis testing strategy with reasoning and one-trial memory, as described above, was implemented in a modified version of the concept identification (CI) model (Bower, 1961; Kendler, 1979). In this strategy, negative feedback after, say, choosing the small circle implies that both features are temporarily removed from the set of possible hypotheses and that subsequently one of the remaining features (large or triangle) is randomly selected as the next hypothesis. Second, as a less efficient strategy, we specified hypothesis testing with one-trial memory (H1) in which only the current hypothesis is rejected temporarily on negative feedback. CI and models both comprise three states: a presolution error state, a presolution correct state, and a learned state. The learned state is absorbing (i.e., it cannot be left once it is entered) and can be entered only after an error response; both of these characteristics follow from the win–stay and lose–shift substrategies. The following parameters were estimated in the CI and H1 models: the learning parameter, the probability of entering the learned state on the first trial (i.e., starting with the correct hypothesis), and the accuracy in the learned state. The remaining probabilities were constrained according to the assumptions of the strategy and the design of the task (e.g., the number of admissible hypotheses, the randomization in blocks of four stimuli).

Fewer assumptions about the learning process are made in the all-or-none (AN) model (Wickens, 1982). This model includes a presolution state and an absorbing learned state. Learning may occur after both errors and correct responses. This implies a relaxation of the strict win–stay, lose–shift, and random selection assumptions that characterize the CI and H1 models. The response accuracy in the learned state and the learning parameter were estimated. The response accuracy in the presolution state was fixed to the chance level probability of .50.

All of the above models are models of learning. To accommodate an excess number of children who do not show improvement during the task, the nonlearning (N) model with a constant accuracy fixed to the chance level probability of .50 was included. Model Nf included one state with a freely estimated constant accuracy (the subscript “f” refers to this free parameter).

Learning strategy results

In this section, we summarize the results of the analysis of the trial-by-trial accuracy data. More detailed results of other candidate models of interest and the model selection procedure are included in the Appendix. The first main result is that the mixture models with multiple components provided a better fit to the data than single-component models in which the learning parameter was free to differ across age groups. The best-fitting and most parsimonious model comprised three components: a fast hypothesis testing component with perfect accuracy in the learned state (CIp, where the subscript “p” stands for perfect), a slow learning all-or-none component with a freely estimated presolution probability (ANf, where the subscript “f” stands for free), and a nonlearning component responding constantly at chance level (N). Fig. 1 shows the estimated parameter values of the best-fitting model graphically. It is important to note that mixture models with these three components fit relatively
better than mixture models with the same number of components but different learning strategies. Notably, replacing the slow learning component or the nonlearning component by the more efficient hypothesis testing with one-trial memory (H1) decreased model fit.

Learning strategy use across age

The estimated mixing proportions of the components differed significantly across the age groups, as shown in Fig. 2. The nonlearning component is present only in the youngest age group. The proportion of the fast hypothesis testing component increased with age. Except for the mixing proportions, the parameters, including the learning parameters and the probabilities of correct responses within the latent states, did not differ across the age groups.

To facilitate comparison, Table 1 shows the percentage of children who reached the learning criterion in each age group. These percentages also increased with age but provide no separation into different strategies, which was achieved with the current statistical analysis.
Learning strategy use at the individual level

Below we examine the relation between the learning strategies and the executive functions working memory and attentional control. To this end, we calculated the posterior probabilities that a given participant used the three strategies based on the participant’s data and the parameter estimates of the three-component ANCIp–CIp–N model (see Appendix). Based on these probabilities, we can arrive at a posteriori classifications of the children according to their most likely component to perform additional analyses within each learning strategy. Accordingly, we obtained the posterior state probabilities for each participant at each trial and determined the most likely latent state at each trial given the participant’s data and the parameter estimates.

Lose–shift behavior

Based on the a posteriori classifications of the participants, we checked whether the 4- and 5-year-olds in the hypothesis testing component simply started with the correct hypothesis. To this end, we examined the responses and the a posteriori most likely state sequences of the 4- and 5-year-olds classified as hypothesis testing. This revealed that all of these children received negative feedback at least once and none of these children started in the learned state on the first trial. This suggests that these children indeed used an efficient hypothesis testing strategy including lose–shift behavior. In the older age groups, a small number of participants did not receive negative feedback (1, 5, 1, and 5 participants in Age Groups 2, 3, 4, and 5, respectively). These participants did not need to engage in lose–shift behavior to master the task.

Response stereotypes

We performed several checks of stereotypical responding. For each participant, we calculated the proportions of three classes of response pairings on two consecutive trials: repetitions of a left response, repetitions of a right response, and alternating responses (left–right and right–left). We inferred that a position stereotype was present if any of these proportions was large in slow learners or in nonlearners. Visual inspection of plots of the proportions revealed that only 6 of the 47 nonlearning children seemed to display a position stereotype (2 location and 4 alternating). To check for biases toward features of the irrelevant dimension, we calculated the repetitions of choices for either of the two features of the irrelevant dimension. Only 1 of the 50 slow learning children had a high proportion of repetitions of a feature. Thus, these results suggest that response stereotypes may account for slow learning or nonlearning in only a few children. The majority of these children did not display response stereotypes.

<table>
<thead>
<tr>
<th>Table 1</th>
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<tbody>
<tr>
<td>Results by age group.</td>
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<table>
<thead>
<tr>
<th>Age group (years)</th>
<th>1 (4–5)</th>
<th>2 (6–7)</th>
<th>3 (8–9)</th>
<th>4 (10–12)</th>
<th>5 (13–14)</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Learning criterion</td>
<td>57.38</td>
<td>88.00</td>
<td>92.00</td>
<td>91.67</td>
<td>95.65</td>
</tr>
<tr>
<td>Mean number of trials</td>
<td>21.80</td>
<td>18.02</td>
<td>16.41</td>
<td>16.97</td>
<td>13.88</td>
</tr>
<tr>
<td>SD number of trials</td>
<td>10.49</td>
<td>7.76</td>
<td>7.55</td>
<td>8.15</td>
<td>5.23</td>
</tr>
<tr>
<td>Mean proportion correct WM</td>
<td>.66</td>
<td>.78</td>
<td>.83</td>
<td>.87</td>
<td>.88</td>
</tr>
<tr>
<td>SD proportion correct WM</td>
<td>.11</td>
<td>.10</td>
<td>.10</td>
<td>.11</td>
<td>.10</td>
</tr>
<tr>
<td>Mean proportion correct AC (C)</td>
<td>.89</td>
<td>.93</td>
<td>.98</td>
<td>.98</td>
<td>.99</td>
</tr>
<tr>
<td>SD proportion correct AC (C)</td>
<td>.10</td>
<td>.11</td>
<td>.02</td>
<td>.02</td>
<td>.01</td>
</tr>
<tr>
<td>Mean response time AC (C)</td>
<td>1037.88</td>
<td>796.11</td>
<td>649.68</td>
<td>551.12</td>
<td>478.61</td>
</tr>
<tr>
<td>SD response time AC (C)</td>
<td>171.44</td>
<td>121.38</td>
<td>135.12</td>
<td>105.49</td>
<td>72.52</td>
</tr>
<tr>
<td>Mean proportion correct AC (I)</td>
<td>.55</td>
<td>.80</td>
<td>.90</td>
<td>.96</td>
<td>.95</td>
</tr>
<tr>
<td>SD proportion correct AC (I)</td>
<td>.28</td>
<td>.25</td>
<td>.14</td>
<td>.04</td>
<td>.12</td>
</tr>
<tr>
<td>Mean response time AC (I)</td>
<td>1174.63</td>
<td>971.24</td>
<td>767.91</td>
<td>634.25</td>
<td>538.00</td>
</tr>
<tr>
<td>SD response time AC (I)</td>
<td>348.59</td>
<td>200.25</td>
<td>164.76</td>
<td>120.53</td>
<td>84.55</td>
</tr>
</tbody>
</table>

Note: Table row names refer to the following results of the three tasks: learning task (% criterion fulfilled, mean and SD of number of trials to criterion), working memory (WM) task (mean and SD of proportion of correct trials), and attentional control (AC) task (mean and SD of proportion of correct trials and of response times (in ms) in the congruent (C) and incongruent (I) conditions).
Feature preferences

Having a preference for an irrelevant feature may hinder the learning process. Therefore, to address the role of such feature preferences, we classified participants as having a feature preference if they responded consistently with one particular feature on at least 5 of the 6 preference trials and on the subsequent first feedback trial. Of the 302 participants, 93 did not show a preference for any of the features, 57 responded consistently with “triangle,” 77 with “circle,” 21 with “small,” and 54 with “large.” Fig. 3 shows the preference proportions of participants in each age group. A latent class analysis on the responses to the first 6 trials yielded four concordant preference patterns, and classification of participants largely overlapped. Having a feature preference correlated significantly with age ($r_{pb} = .38$, $p < .0001$), such that older children were more likely to have a feature preference.

We examined whether young children with a feature preference differed from those without a feature preference with respect to the use of the learning strategies. In the youngest two age groups, the respective group sizes were sufficiently large to test whether the mixing proportions of the three strategies differed across these groups. In the older age groups, we could not test for differences because the proportions of participants without a preference was too small.

The 4- and 5-year-olds with a feature preference differed significantly from those without a feature preference with respect to the use of the learning strategies, that is, the mixing proportions in these groups differ, $\chi^2(2) = 6.33$, $p = .042$. The estimated mixing proportions of the three strategies are shown in Table 2. In 4- and 5-year-olds with a feature preference, the proportion of the hypothesis testing component did not differ significantly from zero and the proportion of nonlearners was twice as large as in the 4- and 5-year-olds without a feature preference. In the 6- and 7-year-olds, children

![Fig. 3. Feature preference by age group. Circles and triangles denote proportions of participants with a preference for circles and triangles, respectively. L and S denote proportions of participants with a preference for large and small stimuli, respectively. The solid line denotes the proportion of participants without any preferences. Preferences above the dotted line are more frequent, and preferences below the dotted line are less frequent, in an age group compared with chance level.](image)

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Estimated mixing proportions of children with (FP) and without (noFP) a feature preference in Age Groups 1 and 2.</th>
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<tbody>
<tr>
<td>Strategy</td>
<td>Age Group 1 (4–5 years)</td>
</tr>
<tr>
<td></td>
<td>FP</td>
</tr>
<tr>
<td>Hypothesis testing ($C_{hp}$)</td>
<td>.02$^a$</td>
</tr>
<tr>
<td>Slow learning ($AN_f$)</td>
<td>.36</td>
</tr>
<tr>
<td>Nonlearning (N)</td>
<td>.62</td>
</tr>
</tbody>
</table>

$^a$ Does not differ significantly from zero, $t = 0.38$, confirmed by $\chi^2(1) = 0.184$, $p = .67$.

$^b$ Estimated on boundary and subsequently fixed to zero.
with a feature preference did not differ significantly from those without a preference with respect to the mixing proportions, $\chi^2(1) = 1.036, p = .31$.

**Working memory**

The proportion of correct responses in the test block of the working memory task ranged from .35 to 1 and increased significantly with age (Kendall’s $\tau = .42, p < .0001$), as expected. Table 1 shows the corresponding mean and standard deviation within each age group. Individual proportions of correct responses were used in the regression analyses reported below.

**Attentional control**

The range of the proportion correct was large in both conditions of the Eriksen flanker task (proportions correct ranged from .64 to 1 in the congruent condition and from 0 to 1 in the incongruent condition). Additional results within age groups are shown in Table 1. The median response times (RTs), calculated of correct trials following on a correct trial, were also highly variable (median RTs ranged from 360 to 1437 ms in the congruent condition and from 391 to 1938 ms in the incongruent condition). At the level of age groups, median RTs decreased with age and the proportion correct increased with age, consistent with previous studies (e.g., Huizinga et al., 2006). However, at the level of individual differences, the comparison of mean or median RTs is problematic given large individual differences in accuracy. These may arise due to differences in the speed–accuracy trade-off. Previous research provided strong evidence for age-related changes in the speed–accuracy trade-off in comparable tasks (Davidson, Amso, Anderson, & Diamond, 2006). If ignored, the speed–accuracy trade-off poses problems in between-participant comparisons and in within-participant comparisons (here, in comparing the performance in the incongruent condition with performance in the congruent condition). In addition, we expected an increase in general processing speed with age. We corrected for the increase in general processing speed with age and for the speed–accuracy trade-off by applying a simplified version of Ratcliff’s diffusion model (see Ratcliff, Thapar, Gomez, & McKoon, 2004, for an application of the original model; see Grasman, Wagenmakers, & van der Maas, 2009, for the simplified version). In the diffusion model for binary decision processes, it is assumed that information accumulation over time is driven by systematic (drift rate) and random influences (Ratcliff et al., 2004). Once the accumulated information exceeds one of two decision boundaries, the decision process is finished and the response system initiates the corresponding response (see, e.g., Grasman et al., 2009, for a detailed description). The separation of the two decision boundaries relates to the speed–accuracy trade-off; a child with a higher value of the decision boundary separation will accumulate more information before making a decision, resulting in longer response times and fewer errors. The drift rate reflects the speed of information accumulation. A child with a large value of the drift rate will reach the correct decision boundary quickly.

The model parameters described below were estimated for each participant from the response time means and variances (of pooled correct and incorrect trials) and from the individual proportion of errors. Where this proportion equaled 0 or 1, it was first rescored to .01 or .99, respectively. Estimation was carried out with the contributed R-package EZ2 (Grasman et al., 2009). The following parameters were estimated for each participant: the drift rate in the congruent condition $v_c$, the ratio $v_I = v_I/v_c$ by which the drift rate in the incongruent condition $v_I$ differs from the congruent condition, and the decision boundary separation $a$. The drift rate in the congruent condition was expected to reflect mainly the general speed of processing. It increased with age, as expected. The boundary separation also increased with age, as expected. We assumed the ratio $v_I = v_I/v_c$ of the two drift rates to reflect attentional control. This is the ratio of information accumulation speed in the incongruent condition ($v_I$) relative to information accumulation speed in the congruent condition ($v_c$). This estimate was used as the predictor of learning strategy in the regression analysis below.

**Relation between learning and executive functions**

To investigate the role of working memory capacity and attentional control in the learning strategies on the discrimination learning task, we carried out sequential regression analyses. The analysis
was carried out over 288 of the 302 participants. In 4 cases the data of the Eriksen flanker task were not recorded due to technical problems, 2 participants had more than 66% missing values in one of the conditions of the Eriksen flanker task, and in 8 participants the EZ2 parameter estimation did not converge. The analysis involved two steps. We regressed the logit transformed a posteriori learning component probabilities of each participant on age in Step 1 and on age, working memory, and attentional control in Step 2.

The results in Table 3 show that with age, the probability of hypothesis testing increases significantly, whereas the probability of nonlearning or slow learning decreases significantly. Adding working memory and attentional control as predictors results in a significant improvement in the variance explained for the hypothesis testing and nonlearning strategies. A higher working memory score is associated with a higher probability of hypothesis testing and a lower probability of nonlearning. A lower attentional control score is associated with a decrease in the probability of hypothesis testing and an increase in the probability of nonlearning.

The stability of the results was checked as follows. The pattern of significant results remained unchanged after the removal of potential outliers. In addition, the same pattern of results was obtained for the hypothesis testing strategy if the best-fitting two-component model was used to generate the a posteriori learning component probabilities of each participant on age in Step 1 and on age, working memory, and attentional control in Step 2.

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Discussion

In this study, we examined the development of discrimination learning in the age range of 4 to 14 years. We also examined the role of feature preferences and the roles of working memory and attentional control in the learning strategies. We analyzed the trial-by-trial accuracy data using mathematical learning models, and we regressed the posterior learning component probabilities on working memory and attentional control measures after controlling for age.

Learning

We identified the best-fitting model of children’s discrimination learning to be a three-component mixture model with a fast hypothesis testing component, a slow all-or-none learning component, and a nonlearning component. The finding of a slow learning and a fast learning component supports the hypothesis of distinct modes of learning and replicates previous results (Block et al., 1973; Raijmakers et al., 2001; Schmittmann et al., 2006). In contrast to previous results, the optimal model included an
additional nonlearning component that may be due to the increased difficulty of the task. This difficulty was introduced by requiring all participants who displayed a preference for a feature of the size dimension (say, a preference for small stimuli) to learn a feature of the shape dimension (say, to always choose the triangle) and vice versa. This manipulation had a significant debilitating effect on learning performance in the youngest age group.

**Hypothesis testing**

The mixing proportion of the hypothesis testing component increased over the age range of 4 to 14 years. The hypothesis testing component can be viewed as a hypothesis testing strategy with reasoning. Once the correct feature has been identified, no more errors are made. Learning occurs after an error, consistent with the lose–shift substrategy. The learning parameter estimate is large, suggesting that negative feedback is used efficiently. One aim of this study was to examine whether young children use efficient hypothesis testing strategies in the simple discrimination learning task. A small, but significant, proportion of even the 4- and 5-year-olds tested hypotheses efficiently using lose–shift and win–stay substrategies. However, this included only those 4- and 5-year-olds who did not respond consistently during the feature preference block. In young children with a feature preference, no fast hypothesis testing was observed. This is remarkable given that consistent responding requires the advanced ability of set maintenance. Although the consistent 4- and 5-year-olds behaved in a manner similar to the children in the older age groups in the preference block, their performance on the learning task was worse than the performance of the inconsistently responding 4- and 5-year-olds. Unlike in 4- and 5-year-olds, having a feature preference for a feature of the irrelevant dimension did not preclude the use of a hypothesis testing strategy in 6- and 7-year-olds and older participants.

**Slow learning**

The slow learning component was characterized by sudden one-step learning. However, on average this sudden one-step learning occurred much later in the sequence of trials than in the hypothesis testing component. In the slow learning component, the correct rule, once acquired, is applied with a very small probability of a mistake. This suggests that slow learning is not due to set maintenance problems and that the win–stay substrategy is applied. The slow learning component is less efficient than hypothesis testing with one-trial memory and less efficient still than testing one hypothesis at a time with zero-trial memory. This suggests that neither the lose–shift nor lose–sample substrategy is applied consistently and/or that the hypotheses are not sampled at random. We discuss possible explanations below.

**Nonlearning**

The nonlearning component was predominant (62%) in the 4- and 5-year-olds with a feature preference. This suggests that the presence of this component in the mixture model originates in the young children’s difficulty in learning a feature of an unpreferred dimension. The nonlearning component was characterized by constant responding at chance level probability. Such responding may originate in a guessing strategy but also in the application of response stereotypes (e.g., consistently choosing left) or other inadequate rules. We detected response stereotypes based on position or features of the irrelevant dimension in only a small number of children. Implicit associative learning could result in small incremental improvements in performance. However, the hypothesis of incremental improvement was not supported; a model of incremental learning did not result in a better fit to the data than the nonlearning model (this check was carried out using WinBUGS; see Lunn, Thomas, Best, & Spiegelhalter, 2000). In sum, we found no evidence that the children who did not reach criterion showed any improvement over the sequence of 48 trials, be it sudden or incremental.

**Executive functions and learning**

We found that, while controlling for age, attentional control and working memory resources predicted the probability of using an efficient hypothesis testing strategy (i.e., the better the control and resources, the higher the probability).
Working memory

The relation with working memory is consistent with adult discrimination learning studies in which additional memory load resulted in appreciably slower discrimination learning (Mutter, Hagg-bloom, Plumlee, & Schirmer, 2006; Siros & Shultz, 1998). The current spatial working memory task requires updating in the sense of a dynamic, goal-directed manipulation of memory content. However, the requirements of the current task go beyond those of common updating tasks (e.g., Salthouse, Atkinson, & Berish, 2003) such as the n-back task in which the information to be kept active by the participants is continuously replaced by new information and in which the amount of information remains the same over trials. In the current task, the new information does not necessarily replace older information. Rather, relevant information accumulates over consecutive trials. Similarly, in the discrimination learning task, information about the relevance of the features accumulates over trials. The ability to recall information from the last trial is a necessary requirement for efficient hypothesis testing. The ability to memorize accumulating information over consecutive trials allows for even more efficient hypothesis testing strategies. The current finding supports the notion that in the tested age range insufficient working memory resources form an obstacle in using an efficient hypothesis testing strategy on the discrimination learning task. Whether other working memory aspects, such as object memory, number span, and word span, explain additional variance in discrimination learning performance remains a question for future research.

Attentional control

Attentional control as measured with the Eriksen flanker task predicted discrimination learning strategy use. In the Eriksen flanker task, participants are required to resist interference from irrelevant and conflicting information in the incongruent condition (Ridderinkhof, van der Molen, & Band, 1997). Prepotent responses that are elicited by irrelevant information need to be inhibited. In this task, the participants know the rule for distinguishing between relevant and irrelevant attributes. In the discrimination learning task, the stimuli are also characterized by relevant and irrelevant attributes, but here the relevance of the attributes needs to be learned from feedback. It is open to debate whether attentional control in performing the Eriksen flanker task requires an inhibition of the irrelevant information, an amplification of the relevant information, or both (e.g., Aron, 2007). The same issue applies to the role of attentional control in the discrimination learning task. However, the results of the current study suggest that the use of an advanced hypothesis testing strategy in discrimination learning is hindered by an inability to resist interference of irrelevant and conflicting information.

Switching

Cognitive flexibility, such as flexibly switching attention between the different features and dimensions, is important in the lose–shift substrategy (e.g., Ashby & Maddox, 2005). The ability to perform an extradimensional rule shift from a frequently applied and reinforced rule to a new rule undergoes significant changes between 2.5 and 13 years of age, as research with the two card sorting tasks DCCS and WCST has shown (Chelune & Thompson, 1987; Huizinga et al., 2006; Kirkham et al., 2003; Zelazo et al., 2003). By 4 years of age, the youngest age group of the current study, children can switch between dimensions when they are explicitly told the correct rule on the DCCS task (Kirkham et al., 2003; Zelazo et al., 2003). Switching between dimensions when children are required to detect the new rule, as in the WCST, seems to undergo significant changes between 7 and 11 years of age, as suggested by decreases in the number of perseverative errors (e.g., Chelune & Thompson, 1987; Huizinga et al., 2006). Due to the design of the discrimination learning task, children received ambiguous feedback (i.e., partial (50%) positive feedback following a choice for a feature of the irrelevant dimension), which might prevent some children from switching between dimensions. In the following, we discuss whether slow learning and nonlearning are attributable to inefficient switching.

Inflexibility of both intra- and extradimensional switching seems unlikely in most young slow learning and nonlearning children. Given general switching inflexibility, a more or less pronounced fixation on a particular rule is expected. In the case of a strong rule fixation that is completely insensitive to feedback, we would expect a high percentage of response stereotypes. However, only a few children displayed response stereotypes. In the case of a weaker fixation, we would expect intrusive errors from responses based on the preferred feature, resulting in a decreased accuracy in the learned
state or an additional state of intermediate accuracy. We found no evidence for either of these types of perseveration. In contrast, inflexibility of extradimensional switching can account for some of the results. Due to the randomization in blocks of four, switching between the two rules of the irrelevant dimension on an error would result in an accuracy below .50 that was found in the slow learning children but not in the nonlearning children. This is remarkable given that a stronger fixation to a dimension would be expected in the children who had an initial preference for a dimension. Informal interviews with some 4- and 5-year-olds that we conducted after the test session suggested that other inadequate rules may have been used. Some of these children described their strategies as, for example, “First I tried the large ones, that was not correct. Then I tried the small ones, but that was not good either. So, I chose the large one and the small one by turns.” Other children reported increasingly complex hypotheses involving one of the dimensions, but not the other, might be a consequence of an inflexibility of extradimensional switching.

These results leave the following possible explanations. First, children may get stuck in the irrelevant dimension rather than in one particular rule. Second, children may come up with more complex inadequate hypotheses. Third, children may respond by guessing. These explanations could hold simultaneously in the slow learning and nonlearning children. However, the first explanation seems to fit the results of the slow learning children, whereas the second and third explanations seem more likely in the nonlearning children, as judged by the estimated accuracies. Latent learning modeling of performance on learning tasks that involve blank trials may help to distinguish between these strategies (Phillips & Levine, 1975). However, performance is expected to suffer in these tasks because blank trial tasks are more demanding. Another promising possibility is the extension of the learning models to include information about the stimuli (Batchelder, 1971).

Limitations and strengths

The cross-sectional nature of the study may limit the interpretation of the results. A longitudinal design would allow stronger inferences concerning the development of learning and its relation with working memory and attentional control. However, a longitudinal study may encounter other complications such as meta-learning effects. In the current study, we used single tasks to measure attentional control and working memory. However, attentional control and working memory are multifaceted. As a reviewer pointed out, it is expedient in future research to explore the selective influence of different aspects of working memory and attention on discrimination learning performance. For instance, in the case of attention, one may ask how the efficiency of three proposed attentional networks of executive conflict resolution, spatial orienting, and alerting contribute to discrimination learning performance (Fan et al., 2002; Posner & Raichle, 1994).

Given the broad age range, one may ask whether we measured the same ability in 4-year-olds and in 14-year-olds with our experimental tasks. Clearly, over these years, children develop in many domains that may be relevant to task performance (e.g., the domains of motor and perceptual skills). This question is related to the issue of task impurity. A psychological task rarely, if ever, measures the single concept of interest. Many developmental differences (including those not of immediate interest) among children in different age groups are likely to have a bearing on the task performance. In addition, the relative contributions of different processes in performing a task might change during development. In the current study, we took certain developmental effects into account. Specifically, we used the diffusion model to analyze performance on the Eriksen flanker task. This model enabled us to separate individual differences in the process of interest (i.e., attentional control) and individual differences in the speed–accuracy tradeoff, conservatism, and in general processing speed. Furthermore, in the latent Markov model analysis of the discrimination learning performance, we estimated the accuracies in the learned state rather than using a fixed learning criterion. This allowed us to test whether age differences in set maintenance or age differences in the frequency of pressing an unintended key may have accounted for slow learning. We ruled out both explanations because the accuracies in the learned states did not differ across age groups.

By applying the method of latent Markov modeling, we could (a) distinguish latent subgroups of different learning processes and estimate their proportions in each age group, (b) determine the most
likely posterior learning strategy, (c) obtain information about the qualitative nature of the learning strategies (e.g., improvement in one step from an initial performance level to an asymptotic level of performance), (d) obtain information about the quantitative characteristics of the learning processes (e.g., by estimating the accuracies in different phases of the learning processes), (e) perform statistical tests of theoretically predicted parameter values and of the significance of age differences, and (f) distinguish different phases in the learning process and different kinds of errors (i.e., informative errors in a hypothesis testing process from errors due to set maintenance problems in the learned state).

Directions for future research

Above we discussed possible ways in which working memory and attentional control may be related to discrimination learning. Such hypotheses about the causal processes can be tested by manipulating the task (e.g., by selectively introducing memory aids for different subtasks of the learning task, by varying the saliency of the stimulus features within and between dimensions). In addition, one may study whether training in working memory capacity and attentional control (e.g., Diamond, Barnett, Thomas, & Munro, 2007) leads to an improvement in discrimination learning performance. Finally, the extent to which the current findings generalize to other learning tasks and learning contexts remains to be studied.

Conclusion

To our knowledge, this is the first study to investigate the role of the executive functions working memory and attentional control in different latent strategies of learning a simple discrimination of an unpreferred dimension. The current findings are consistent with the results of previous studies that revealed multiple learning modes in discrimination learning. A model with the three latent groups of hypothesis testing, slow learning, and nonlearning provided the best and most parsimonious fit to the data. The proportion of efficiently hypothesis testing children increased with age, and nonlearners were significantly present only in the 4- and 5-year-olds. The 4- and 5-year-olds who showed a feature preference and were forced to learn a rule of their unpreferred dimension appeared to be unable to engage in an efficient hypothesis testing strategy. However, a small group of the 4-and 5-year-olds who did not show a feature preference engaged in efficient hypothesis testing. Spatial working memory and attentional control significantly predicted posterior learning strategy probabilities after controlling for age.

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Appendix

Learning model fit and selection

We fit various models to the time series data by means of maximum likelihood estimation using the R-package depmix (Visser, 2007). Relative fit of the models was evaluated with likelihood ratio tests where appropriate (e.g., Azzalini, 1996). Otherwise, we compared models using information criteria AIC (Akaike’s information criterion) and BIC (Bayesian information criterion) (see Burnham & Anderson, 2002). Relatively lower AIC or BIC indicates a better fit.

The different learning strategies, as described above, were implemented in the following component models: the concept identification model with constraints on the transitions between
presolution states (CI) and without these constraints (Clf, where the subscript “f” stands for freely estimated), the hypothesis testing with one-trial memory model (H1), the all-or-none model with presolution accuracy fixed to .50 (AN) and with freely estimated presolution accuracy (ANf), and the two nonlearning models N (accuracy fixed to the expected value of .50) and Nf (freely estimated constant accuracy).

Table A1 shows summarized results of selected models of interest grouped into six categories. Models in the first category consist of a single-component model in which the learning parameter was free to differ across the five age groups. As mentioned above, the component models were fit to the data not only separately but also in mixture models that consisted of different combinations of the component models. Mixture models with two and three components (Categories 2 and 3, respectively) provided a better fit to the data, as indicated by AIC and BIC. In these models, the parameters were equal across age groups. In other words, heterogeneity in the sample is better described by categorical differences between latent groups, which use different learning strategies, than merely by continuous differences in learning efficiency among age groups. The two best-fitting models in Categories 2 and 3 were a mixture model with an ANf component and a Clp component, where the subscript “p” stands for perfect accuracy in the learned state (preferred by BIC), and the same model with an additional nonlearning N component (preferred by AIC). Because BIC generally favors more parsimonious models, it is not surprising that BIC identifies the model without the N component as the model of choice. These two mixture models fit relatively better than mixture models that have the same number of components but differ in their constituent components. For instance, replacing the slow learning ANf component in the mixture model ANf–CI–N by an H1 component results in a relatively worse model fit (see model H1–CI–N).

To examine whether the probabilities of using the different learning strategies change with age, we compared the best-fitting models from Categories 2 and 3 with the respective 5-age group (5g) models in Category 4. In the latter models, the mixing proportions were free to vary among the 5 age groups, whereas the remaining parameters were constrained to be equal across age groups. The mixing proportions differed significantly across age groups. In contrast, learning parameters and observation probabilities did not differ significantly across age groups (those models are not included in Table A1). Still, AIC favors the three-component model, and BIC favors the two-component model. Judged by AIC and BIC, these two models provided a better fit than all exploratory one- to seven-state models (see Category 6; results of the best exploratory models are reported). In the two-component model, all mixing proportions differed significantly from zero. This implies, inter alia, that even in the youngest age group, a given percentage of children learned rationally. In the three-component model, all mixing proportions differed from zero except those of the nonlearning component in Age Groups 2 to 5. Therefore, we fixed these four mixing proportions to zero in a model, which we designate ANf–Clp–N1 5g. Both AIC and BIC favor this mixture model over the two-component model ANf–CI 5g.

In Category 5, we examined whether young children with a feature preference (FP) differed from those without a feature preference (noFP) with respect to the use of the learning strategies. In the two youngest age groups, the FP and noFP groups were sufficiently large to test this. First, we split Age Group 1 into two groups: FP1 and noFP1. Together with the four older age groups, this amounted to a total of six distinct groups. In model ANf–Clp–N1 6g, the mixing proportions of the components ANf and Clp were estimated freely in all six groups and the mixing proportion of component N was estimated freely in the FP1 and noFP1 groups. Remaining parameters were constrained to be equal across all groups. The mixing proportions of the three component models differed significantly between the FP1 and noFP1 groups, $\chi^2(2) = 6.33, p = .042$. In addition, the mixing proportion of the Clp component did not differ significantly from zero in the FP1 group, $t = 0.38$ (also model ANf–Clp noFP1 2345 7g, $\chi^2(1) = 0.184, p = .67$). In Age Group 2, the mixing proportions of children with and without a feature preference were not significantly different (model ANf–Clp–N1 7g, $\chi^2(1) = 1.036, p = .31$). To conclude, the mixture model with the three components ANf, Clp, and N provided the best fit to the data. The mixing proportions of these components differed significantly across age groups (see Fig. 2). Within Age Group 1, the mixing proportions of the components also differed between the FP1 and noFP1 groups, that is, depending on whether a child had a feature preference or not (see Table 2).
Table A1
Learning model fit indexes, log likelihood, and degrees of freedom.

<table>
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<tr>
<th>Category</th>
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<th>Model</th>
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<th>AIC</th>
<th>BIC</th>
<th>df</th>
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<td>3-state exploratory</td>
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<td>-3694.84</td>
<td>7247.69</td>
<td>7444.20</td>
<td>29</td>
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</tbody>
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Note: logL, log likelihood; AIC, Akaike’s information criterion; BIC, Bayesian information criterion; df, degrees of freedom. Superscripts indicate that a component was estimated only in selected age groups; for example, in N1 the nonlearning component applies only to Age Group 1. The subscript “p” indicates perfect accuracy in the learned state. The subscript “f” indicates freely estimated resolution accuracy.

References
