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Preschoolers can form abstract rule representations regardless of cognitive flexibility

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ABSTRACT

The abstractness of rule representations in the pre-switch phase of the Dimensional Change Card Sorting (DCCS) task was studied by letting 3- and 4-year-old children perform a standard DCCS task and a separate generalization task. In the generalization task, children were asked to generalize their sorting rules to novel stimuli in one of three conditions. In the *relevant change* condition, values of the relevant dimension changed; in the *irrelevant change* condition, values of the irrelevant dimension changed; and in the *total change* condition, values of both dimensions changed. All children showed high performance on the generalization task in the relevant change condition, implying an abstract rule representation at the level of dimensions ("same colors go together"). Performance in the relevant change condition was significantly better (and faster) than performance in the other two conditions. Children with high cognitive flexibility (switchers on the DCCS task) more often switched their attention to the irrelevant dimension in the generalization task only if values of the irrelevant dimension changed. Children with low cognitive flexibility (perseverators) were more often inconsistent in their sorting on the generalization task if values of both dimensions changed. The difference in performance on the DCCS task between switchers and perseverators seems to result from the processes that operate on the learned sorting rules and not from the abstractness of the rule representations children have.

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Introduction

Flexibility is an important ability in the current rapidly changing society. One should be able to change plans in response to relevant changes in the environment and, complementarily, to maintain activities when changes in the environment are irrelevant. Cognitive flexibility is improving substantially during the preschool years (Carlson, 2005), and the Dimensional Change Card Sorting (DCCS) task is a widely used paradigm to study this in preschoolers (Zelazo, 2006). In this task, children are required to sort two bivalent test cards according to shape or color on two stacks marked by target cards. Each test card matches one target card on color and the other target card on shape. After sorting a series of test cards according to one dimension (e.g., color), children are asked to sort the same test cards according to the other dimension (e.g., shape). Nearly all 3- and 4-year-olds sort correctly in the first phase of the task (the pre-switch phase) regardless of which dimension is presented first. Most 3-year-olds perseverate in the second phase of the task (the post-switch phase) by sorting test cards according to the initial dimension, whereas most 4- and 5-year-olds switch immediately to the new dimension when asked to do so (Kirkham, Cruess, & Diamond, 2003; Perner & Lang, 2002; Zelazo, Frye, & Rapus, 1996).

A number of theoretical frameworks have been proposed to explain perseverative behavior at the DCCS task. According to *attentional inertia* theory, perseverators may know the new rules they should be following but fail to suppress attention to the pre-switch relevant information (Kirkham et al., 2003). The *activation deficit* account assumes that perseverators fail to activate previously inhibited information (Chevalier & Blaye, 2008; Müller, Dick, Gela, Overton, & Zelazo, 2006). According to the *redescription* account, perseverators can conceptualize a stimulus in a single way (i.e., using the pre-switch rules) but fail to redescribe the stimulus in another way (i.e., according to the post-switch rules) (Perner & Lang, 2002). The *cognitive complexity and control* (CCC) theory assumes that perseverators cannot formulate and use a higher order rule for selecting which pair of rules (color rules or shape rules) must be used on a particular trial (Zelazo, Müller, Frye, & Marcovitch, 2003). Finally, the *competing memory systems* theory supposes that flexible behavior depends on the competition between active and latent memory traces. Perseveration occurs when an active memory trace of the current sorting rules is not strong enough to compete against a latent memory trace of the previously relevant sorting rules (Munakata, 1998).

The competing memory systems account hypothesizes that there is a fundamental difference in rule representations between switchers and perseverators (Cohen & Servan-Schreiber, 1992; Morton & Munakata, 2002). The active memory traces of switchers are thought to rely on later developing prefrontal cortical regions that represent the sorting rules in a more abstract form, whereas the latent memory traces of perseverators are thought to rely more on earlier developing posterior cortical regions that represent the sorting rules in a more stimulus-specific form (Patalano, Smith, Jonides, & Koeppe, 2001). Unlike the competing memory systems account, the first four theoretical frameworks assume that perseverators and switchers do not necessarily differ in how they represent the sorting rules. Instead, switchers and perseverators are supposed to differ in the processes that operate on the learned sorting rules (e.g., inhibition, reactivation, redescription, reflection).

Representations of sorting rules in the DCCS task

Knowledge about the level of abstraction of the representations of children's sorting rules is particularly relevant to further understanding of processing in the DCCS task. Hence, an important aim of the current study was to study the abstractness of the rule representations of children after the pre-switch phase of the DCCS task when they need to switch rules. The rule representations in the DCCS task could theoretically have three levels of abstraction. The least abstract level is a representation at the level of the specific stimuli. Sorting rules can then, for example, be formulated as "the red car goes with the red rabbit and the blue rabbit goes with the blue car." The second level is a representation at the level of the values of dimensions. Sorting rules can then, for example, be formulated as "red goes with red and blue goes with blue." Finally, the most abstract level is a representation at the

level of dimensions. The sorting rule can then, for example, be formulated as "same colors go together."

A standard way to study the level of abstraction is by generalization (Huang-Pollock, Maddox, & Karalunas, 2011; Johansen & Palmeri, 2002; Medin & Schaffer, 1978; Nosofsky, Palmeri, & McKinley, 1994). Generalization is the adaptive application of past experiences to new circumstances. Successful generalization requires recognition of the similarities between those past experiences and the current situation, and abstraction is exactly the recognition of such similarities between different objects or situations (Son, Smith, & Goldstone, 2008). We adopt this concept of abstractness to study children's rule representations.

Kharitonova, Chien, Colunga, and Munakata (2009) studied the rule representations of children in the post-switch phase of the DCCS task by asking 3-year-olds to generalize their post-switch sorting rules to novel stimuli in an additional third phase following a standard DCCS task. Switchers applied the (correct) rules they were using in the post-switch phase more consistently to novel cards than perseverators applied the (incorrect) rules they were using in the post-switch phase. Based on these results, Kharitonova and colleagues assumed a link between active representations that support switching and abstract representations that support generalization. However, it is important to note that the generalization task these authors used in their study could not be solved by the application of abstract sorting rules (as we defined above) at the level of dimensions alone ("same colors go together") or by the application of sorting rules at the level of the values of dimension alone ("red goes with red and blue goes with blue"). The target cards remained constant throughout the experiment and depicted a red truck and a blue flower. The test cards used in the pre-switch phase and the post-switch phase of the task depicted blue trucks and red flowers (thereby exactly matching each target card on one dimension), whereas the novel test cards used in the additional third phase of the task only approximately matched each target card on one dimension (e.g., a turquoise television and an orange ball). Hence, in addition to the application of abstract sorting rules, children also needed to make a similarity match. The sorting rules that would lead to successful performance in the generalization task of Kharitonova and colleagues' study could be formulated as "approximately same colors go together" or "something like red goes with red and something like blue goes with blue." A distinction between the two levels of abstraction of the representations of sorting rules as we defined it cannot be made with this task.

Kharitonova and Munakata (2011) studied the generality and specificity of the link between flexibility and abstraction found in the study of Kharitonova et al. (2009). Flexibility was measured by means of a standard DCCS task, whereas abstraction was measured in terms of selecting which stimulus did not belong in an odd-one-out task. This last task requires the ability to form abstract rules (that link three stimuli together in contrast to the odd one) from examples. The link between flexibility and abstraction was general across the dimension used in the odd-one-out task (similar to or different from the dimensions used in the DCCS task) and was general across the ordering of the two tasks. Good performance on the flexibility and abstraction measures did not extend to all cognitive tasks, suggesting that the link is specific to tasks that require the use of flexible and abstract representations.

Hanania (2010) also studied children's representations of sorting rules in the post-switch phase of the DCCS task with a standard DCCS task followed by an additional third phase with stimuli with changed values on both dimensions. Approximately a third of the children who perseverated in the post-switch phase of the DCCS task successfully switched when novel stimuli were presented, whereas two thirds of the perseverators continued to sort according to the pre-switch sorting rules in all three phases of the task. Hanania concluded that there are two types of perseverators: children who perseverate at the level of dimensions (children who continued to sort according to the initial dimension in the additional third phase) and children who perseverate at the level of the values of dimensions (children who successfully switched in the additional third phase). However, the additional third phase in Hanania's study did not require an abstract rule representation. By referring to the new values of the relevant sorting dimension at the start of the third phase (e.g., "now the green ones go here with the green ones and the yellow ones go here with the yellow ones"), children were given the new sorting rules at the level of the specific values, making an abstract representation of the sorting rules at the level of dimensions unnecessary.

Zelazo et al. (2003) studied children's representations of sorting rules with several versions of the DCCS task in which the values of the dimensions of the test and target cards changed between the pre-switch phase and the post-switch phase of the task. In the total change version, the values of both dimensions (color and shape) of the test and target cards changed. In the partial change version, only the values of the dimension that was relevant in the post-switch phase changed. In the negative priming version, only the values of the dimension that was relevant in the pre-switch phase changed. Children performed better on the total change version than on the standard DCCS task, and this was taken as evidence that children perseverate DCCS sorting rules on the specific values of the dimensions and not on the dimensions themselves. However, a large proportion of children failed in the total change version (21%, 37%, and 31% in Experiments 7, 8, and 9, respectively). Moreover, children performed better on the total change version than on the negative priming version. These results cannot be explained by a representation of the sorting rules at the level of values of dimensions or at the level of dimensions because in both versions the values of the dimension that is relevant in the pre-switch phase changed. Yerys and Munakata (2006) provided a different explanation for these results. In the total change version (and not in the negative priming version), the values of the dimension that is relevant in the post-switch phase changed. These changing values would draw attention to the correct sorting dimension in the post-switch phase, and this would make switching easier. The trend for a significant difference between the partial change version and the standard DCCS task (Zelazo et al., 2003) supports this idea. Multiple explanations for the results of Zelazo et al. (2003) are possible, making it difficult to draw clear conclusions about the abstractness of rule representations in the DCCS task on the basis of these experiments.

The current study

The studies of Kharitonova et al. (2009) and Hanania (2010) investigated children's rule representations in the post-switch phase of the DCCS task. The goal of the current study was to assess the abstractness of children's rule representations in the pre-switch phase of the DCCS task, that is, just before rule switching. Kharitonova and Munakata (2011) also studied children's abstraction ability directly following the pre-switch phase or before the switch task, but they did not focus specifically on the representation of the rules learned in the pre-switch phase based on the experimenter's instruction. The latter was the focus in the current study. This research question was studied by asking children to generalize their baseline sorting rules to new stimuli without making a switch first. This is analogous to procedures for testing representations in category learning studies (Ashby & Ell, 2001). By combining a generalization task with a separate standard DCCS task, we also studied the relationship between the abstractness of the representation of the pre-switch sorting rules and the ability to switch. In the study of Kharitonova and Munakata (2011), children's abstraction ability was measured with an odd-one-out task requiring forming an abstraction from examples. To make a more direct measure of the abstractness of children's rule representations in the pre-switch phase of the DCCS task, we designed a generalization task that resembled the DCCS task as much as possible. The generalization task consisted of two phases. The first phase of the generalization task (the baseline phase) was equivalent to the pre-switch phase of the DCCS task. In the second phase of the generalization task (the generalization phase), the sorting rules of the baseline phase needed to be generalized to test and target cards with changed values on one or both dimensions.

To discriminate the three theoretically possible levels of abstraction of the representations of the sorting rules, three conditions of the generalization task were constructed based on the change versions of the DCCS task of Zelazo et al. (2003). In the *relevant change* condition, only the values of the relevant sorting dimension change. If children need to sort according to color in the baseline phase, the colors of the test and target cards change in the generalization phase. In the *irrelevant change* condition, only the values of the irrelevant dimension change. If children need to sort according to color in the baseline phase, the shapes of the test and target cards change. In the *total change* condition, the values of both dimensions change. If children need to sort according to color in the baseline phase, the shapes and colors of the test and target cards change. Children with a rule representation at the level of the specific stimuli are expected to show low performance in all three conditions. Children with a rule representation at the level of the values of dimensions are expected to show low

performance in the relevant change condition and the total change condition and to show high performance in the irrelevant change condition. Children with a rule representation at the level of dimensions are expected to show high performance in all three conditions.

Yerys and Munakata (2006) would predict differences in performance on the generalization task among conditions even in the case where the abstractness of the rule representations was equal for all children; changes in the values of one dimension would draw attention toward this dimension. Changes in the dimension that is irrelevant in the pre-switch phase of the DCCS task would draw attention to this dimension, making switching easier because that dimension is relevant in the post-switch phase. In the generalization task, children do not need to make a switch but need to continue sorting according to the same dimension while target and test cards change. If changes in the relevant sorting dimension draw attention to that dimension, maintaining to sort according to that dimension would be easy. On the other hand, changes in the irrelevant sorting dimension may make it more difficult to maintain sorting according to the relevant sorting dimension.

In the current study, we first tested the level of abstraction of the pre-switch rule representations children have by applying a generalization task in multiple conditions that require different levels of abstraction. Second, we studied the possible relationship between abstraction and flexibility by relating performance on the generalization task to performance on a standard DCCS task.

Method

Participants

A total of 167 children participated in this study: 77 3-year-olds (M_{age} = 42.0 months, SD = 3.1, range = 36–47, 41 boys and 36 girls) and 90 4-year-olds (M_{age} = 53.2 months, SD = 3.5, range = 48–59, 45 boys and 45 girls). We tested another 47 children, but their data could not be used because they did not pass the first phase of the generalization task (n = 13), the first phase of the DCCS task (n = 13), or both (n = 11); because they refused to complete testing (n = 6); or due to experimenter error (n = 4). Children were recruited from day-care centers and primary schools in The Netherlands. Informed consent was obtained from the parents of all children who participated.

Design

Children were randomly assigned to one of three conditions: the *relevant change* condition (n = 58, M_{age} = 48.1 months, SD = 6.5, range = 36–59, 30 boys and 28 girls), the *irrelevant change* condition (n = 57, M_{age} = 48.0 months, SD = 6.2, range = 36–59, 31 boys and 26 girls), or the *total change* condition (n = 52, M_{age} = 48.1 months, SD = 6.9, range = 36–59, 25 boys and 27 girls). In all three conditions, children were administered a DCCS task and a generalization task. The DCCS task was a standard version of the DCCS task and was exactly the same in all three conditions. However, there was a difference among the generalization tasks in the three conditions. In the relevant change condition, the values of the sorting dimension that is relevant in the generalization task changed. In the irrelevant change condition, the values of the irrelevant dimension changed. In the total change condition, the values of both the relevant and irrelevant dimensions changed. If children sorted according to color in the generalization task, they switched from sorting according to color to sorting according to shape in the DCCS task. If children sorted according to shape in the generalization task, they switched from sorting according to shape to sorting according to color in the DCCS task. Two sets of cards were used. The order of the presentation of the two tasks, the order of the two sorting dimensions (color and shape), and the order of the sets of cards were counterbalanced and crossed within each Age × Gender cell.

Materials

The experiment was conducted using a laptop computer with a separate touch-screen monitor. The tasks were programmed using the software package Authorware (Version 7.0). Stimuli were presented against a dark gray background (1024 × 768 pixels). In both tasks, two light gray sorting stacks

(220 × 270 pixels) were presented in the bottom left and right corners of the screen. Above them, the target cards (200 × 163 pixels) were depicted. A test card (270 × 220 pixels) appeared in the bottom center of the screen on each trial when the experimenter pressed a key on the laptop computer. Children sorted the test cards by touching the appropriate sorting stack or target card on the touch-screen monitor. See Fig. 1 for an example of the computer screen.

Two sets of cards were used. Cards in Set A depicted stimuli with the following shapes and colors: rabbit, chicken, pig, fish, green, yellow, orange, and purple. Cards in Set B depicted stimuli with the following shapes and colors: frog, snail, butterfly, cat, red, blue, brown, and pink. For half of the children, target and test cards in the DCCS task depicted green and yellow rabbits and chickens and target and test cards in the baseline phase of the generalization phase depicted red and blue frogs and snails. For the other half of the children, target and test cards in the DCCS task depicted red and blue frogs and snails and target and test cards in the baseline phase of the generalization task depicted green and yellow rabbits and chickens. The target and test cards in the generalization phase of the generalization task were different in the three conditions. In the relevant change condition, only the values of the relevant sorting dimension changed. For example, if a child sorted yellow rabbits and green chickens according to color in the baseline phase of the task, the color rules needed to be generalized to purple rabbits and orange chickens in the generalization phase of the task. In the irrelevant change condition, only the values of the irrelevant sorting dimension changed. If a child sorted yellow rabbits and green chickens according to color in the baseline phase of the task, the color rules needed to be generalized to yellow fish and green pigs in the generalization phase of the task. In the total change condition, the values of both the relevant and irrelevant dimensions changed. If a child sorted yellow rabbits and green chickens according to color in the baseline phase of the task, the color rules needed to be generalized to purple fish and orange pigs in the generalization phase of the task. See Fig. 2 for examples of target and test cards used in the generalization and DCCS tasks in the three conditions.

Procedure

Children were tested individually in a quiet room in their day-care center or primary school. Once the child was comfortable with the experimenter, the touch screen was introduced and the experimenter verified the child's knowledge of the colors and shapes used in the tasks.

The experimenter then explained the rules of the baseline phase of the generalization task (sorting according to color or sorting according to shape) and demonstrated the sorting of the two test cards that would be used in the baseline phase. The child was then asked to sort six test cards himself or herself. In this first phase, the two different test cards were presented in pseudo-random order, so that no test card was presented more than twice in a row. On alternating trials, the experimenter either reminded the child of the relevant sorting rules or asked the child knowledge questions (e.g., "Where do the green ones go in the color game?"). Immediately after the repetition of the rules or the knowledge question, a test card was presented. The experimenter labeled the test card with the
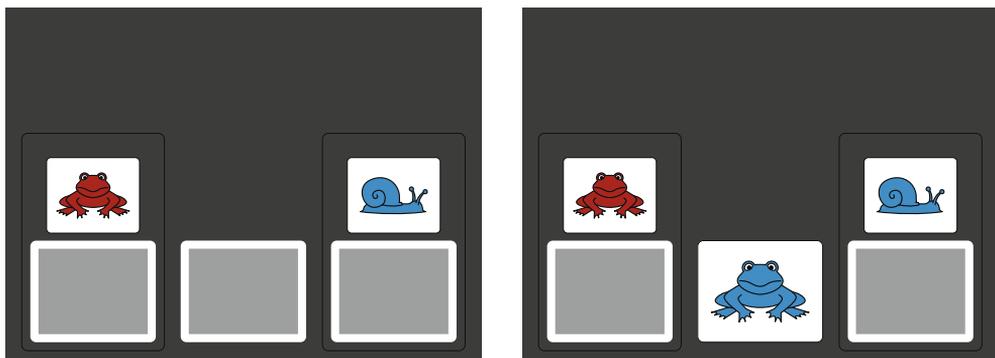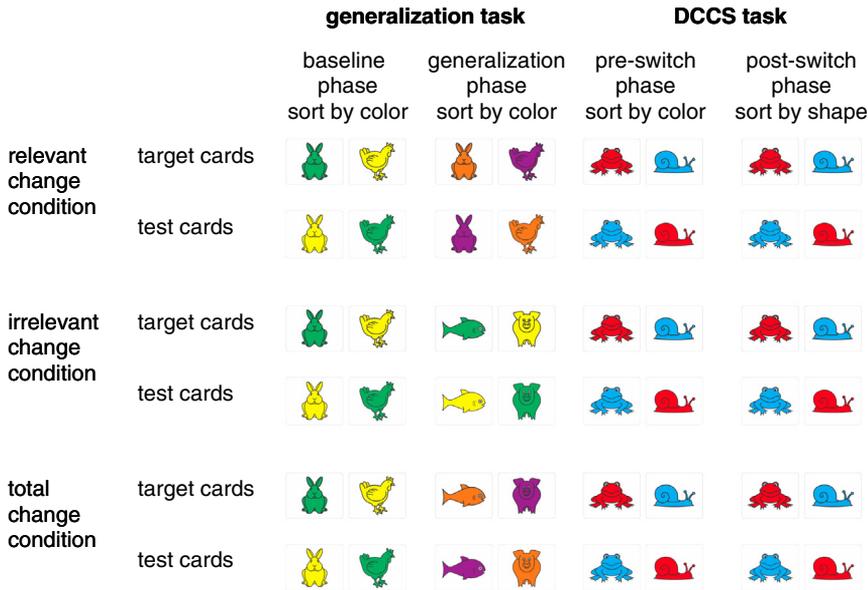

Fig. 1. Example of the computer screen.

Fig. 2. Examples of target and test cards used during the different phases of the generalization task and the DCCS task in the three conditions.

relevant dimension only (e.g., "This is a yellow one; where does it go?"). Children were given feedback on their response to the knowledge questions but not on their sorting. A child needed to sort at least five of the six test cards correctly to pass the baseline phase. At the start of the second phase of the generalization task (the generalization phase), the target and test cards changed. Six trials were administered in pseudo-random order again. The rules of the game were not repeated, but the child was encouraged to keep on playing the same game. The experimenter did not label the test cards but simply asked, "Where does this one go?" As in the baseline phase, children were not given feedback on their sorting in the generalization phase.

After a break of approximately 5 min, during which the experimenter and child read a book, the second task was administered. The experimenter explained the rules of the new game (sorting according to color or sorting according to shape) and demonstrated the sorting of the two test cards that would be used in the first phase of the DCCS task (the pre-switch phase). The pre-switch phase was administered in exactly the same way as the baseline phase of the generalization task. The two different test cards were presented in pseudo-random order, and on alternating trials the experimenter either reminded the child of the relevant sorting rules or asked knowledge questions. When a test card was presented, the experimenter labeled the card with the relevant dimension only, and children were given feedback on their response to the knowledge questions but not on their sorting of the test cards. Six pre-switch trials were administered. A child needed to sort at least five of the six test cards correctly to pass the pre-switch phase. At the start of the second phase of the DCCS task (the post-switch phase), the rules of the new game were explained but not demonstrated. Six post-switch trials were administered with the same target and test cards and in exactly the same way as the pre-switch trials. The order of the presentation of the two tasks and the order of the two sorting dimensions were counterbalanced.

Statistical approach

To get a more precise picture of children's behavior in the DCCS task and the generalization task, the statistical approach taken in the current study was fitting latent Markov models (Rabiner, 1989; Van der Pol & Langeheine, 1990; Visser, 2011) to the trial-by-trial accuracy data of the post-switch

phase of the DCCS task and to the trial-by-trial accuracy data of the generalization phase of the generalization task using the package depmixS4 (Visser & Speekenbrink, 2010) for the R statistical programming environment (R Development Core Team., 2009). It is important to note that there are different ways of responding in the post-switch phase of the DCCS task. One can sort consistently according to the (correct) post-switch relevant dimension, one can sort consistently according to the (incorrect) pre-switch relevant dimension, one can make a transition from one dimension to the other dimension after some trials, or one can sort inconsistently. These behavioral modes could only be distinguished using modeling techniques to create latent groups. Standard analyses of DCCS task data use sum scores of the post-switch phase, which cannot make a distinction between the last two behavioral modes. We expected to find different ways of responding in the generalization phase of the generalization task as well.

van Bers, Visser, van Schijndel, Mandell, and Raijmakers (2011) showed that fitting latent Markov models is a reliable statistical method to classify post-switch DCCS data into latent subgroups. We used this method here as well to distinguish possible latent performance groups for the DCCS task as well as for the generalization task. Moreover, with these latent Markov models, we could also quantify possible transitions between latent states over the course of the post-switch trials or generalization trials. The latent Markov models were defined by a number of parameters that allowed us to identify the nature of the latent states: response probabilities, initial probabilities, and transition probabilities. The response probability is the probability of a correct response, conditional on being in a certain latent state. The initial probability is the probability of being in a certain latent state at the first trial. The transition probability is the probability of moving to another latent state, conditional on being in a certain latent state.

We fitted several latent Markov models to the trial-by-trial data of the generalization phase of the generalization task: models with different numbers of latent states and models with and without transitions between the latent states. We fitted these models for the three conditions separately. Subsequently, by the application of multi-group models, we combined the three separate models and tested whether model parameters could be set equal among the three conditions. This way we could test for possible differences among the three conditions.

We also fitted several latent Markov models to the trial-by-trial data of the post-switch phase of the DCCS task: models with different numbers of latent states and models with and without transitions between the latent states. We fitted these models for all post-switch data together. For a more elaborate description of the different latent Markov models, see van Bers et al. (2011).

Models were fit to the data by calculating maximum likelihood estimates of the parameters. We used model selection methods (information criteria and log-likelihood difference tests) to determine which model best described the trial-by-trial data of the post-switch phase of the DCCS task and of the generalization phase of the generalization task. Hypotheses concerning the number of latent states in the latent Markov models were tested with two commonly used information criteria: Akaike information criterion (AIC; Akaike, 1974) and Bayesian information criterion (BIC; Schwarz, 1978). Lower AICs or BICs indicated a better fitting model. Hypotheses concerning particular values of parameters were tested by means of log-likelihood difference tests (e.g., Wickens, 1982). If the test was significant, the null hypothesis of equal model fit was rejected and the less parsimonious model was preferred. Otherwise, the more parsimonious model was preferred.

Results

No significant effects were found for gender, order of the two sets of cards, or order of the two sorting dimensions. Therefore, further results are collapsed across those variables. No significant effects were found for the order of the two tasks either. There was no significant difference in the percentage of children passing the generalization phase of the generalization task between the children who performed the generalization task first and the children who performed the DCCS task first in the relevant change condition (100% of the children passed), in the irrelevant change condition, $\chi^2(df = 1, n = 57) = 0.004$, $p = .95$, or in the total change condition, $\chi^2(df = 1, n = 52) = 0.59$, $p = .42$. There was also no significant difference in the distribution of the number of switchers, perseverators, and children in

transition between the children who performed the generalization task first and the children who performed the DCCS task first, $\chi^2(df = 2, N = 167) = 3.34$, $p = .19$. This means that there was no difference in performance on the switch task between the children who performed the generalization task first and the children who performed the DCCS task first. Therefore, results are collapsed across this variable as well.

Representation of pre-switch sorting rules

In the generalization phase of the generalization task, most of the children either responded to the baseline sorting rules on zero or one (3.6%, low performers), or five or six (90.4%, high performers), of the six generalization trials. Nearly all children in all three conditions of the generalization task showed high performance. In the relevant change condition, all children (100%) showed high performance. A small group of children in the irrelevant change condition (10%) and the total change condition (14%) showed low performance. In conclusion, we can state that all children who learned to execute sorting rules in the pre-switch phase formed a representation at the level of dimensions (i.e., "same colors go together") because all children successfully generalized in the relevant change condition. Hence, possible differences between conditions could not be explained by the abstractness of sorting rules.

Differences between conditions on generalization task

Standard analyses

Given the bimodal nature of the data, nonparametric analyses (chi-square tests) were used to analyze the data. Children who sorted at least five of the six generalization trials according to the baseline sorting rules were considered to have passed the generalization phase. Table 1 shows the numbers of children passing the generalization phase in the three conditions. All 58 children in the relevant change condition passed the generalization phase, 47 of the 57 children in the irrelevant change condition passed the generalization phase, and 46 of the 52 children in the total change condition passed the generalization phase. There was a significant difference in performance among the three conditions, $\chi^2(df = 2, N = 167) = 10.55$, $p < .01$. Planned comparisons revealed that more children passed the generalization phase in the relevant change condition than in the irrelevant change condition, $\chi^2(df = 1, n = 115) = 11.15$, $p < .01$, and in the total change condition, $\chi^2(df = 1, n = 110) = 7.08$, $p < .01$.

Model-based analyses

To get a more precise picture of the differences between the three conditions, we first fitted four different latent Markov models to the trial-by-trial data of the generalization phase of the generalization

Table 1
Numbers of children passing the generalization phase of the generalization task in the three conditions for the children categorized as perseverators, in transition, or switchers.

Group	Relevant change condition		Irrelevant change condition		Total change condition	
	Pass	Fail	Pass	Fail	Pass	Total
Perseverators (*n* = 42)	18 (100)	0 (0)	13 (93)	1 (7)	8 (80)	2 (20)
In transition (*n* = 22)	6 (100)	0 (0)	11 (92)	1 (8)	3 (75)	1 (25)
Switchers (*n* = 103)	34 (100)	0 (0)	23 (74)	8 (26)	35 (92)	3 (8)
Total (*N* = 167)	58 (100)	0 (0)	47 (82)	10 (18)	46 (88)	6 (12)

Note: Percentages are in parentheses. Each column shows the number of children (and percentage) passing the generalization phase in that condition (left) and the number of children failing the generalization phase in that condition (right). Children who sorted at least five of the six generalization trials according to the baseline sorting rules were considered to have passed the generalization phase.

task for each condition separately: a one-state model, a two-state model with two transitions between the two states, a two-state model with one transition, and a two-state model without transitions. Table 2 shows the fit indexes of the different models in the three conditions. In the relevant change condition, the model with one state fitted the data better than the models with two states (cf. AIC and BIC in the upper section of Table 2). In the irrelevant change condition, the models with two latent states fitted the data better than the model with one latent state (see middle section of Table 2). The full model with two latent states and bidirectional transitions between the two latent states fitted the data best and was preferred, although the differences in fit among the three models with two states were very small. In the total change condition, the models with two latent states fitted the data better than the model with one latent state (see lower section of Table 2). The two-state model with only one transition (from the low-performing group to the high-performing group) fitted the data best and was preferred.

To test whether the response probabilities for the two latent states of the three preferred models differed among conditions, we fitted three different multi-group latent Markov models to the trial-by-trial data of the generalization phase of the generalization task (see Table 3): a model with equal response probabilities in both latent states, a model with equal response probabilities in the latent state with a high response probability and unequal response probabilities in the latent state with a low response probability, and a model with unequal response probabilities in both latent states. The model with equal response probabilities in the latent state with a high response probability but unequal response probabilities in the latent state with a low response probability was the simplest model that did not fit the data significantly worse than the full model with unequal response probabilities in both latent states. Therefore, this model was preferred as the most parsimonious, best fitting model. A graphical representation of the optimal multi-group latent Markov model is shown in Fig. 3, which also shows the parameter estimates. In conclusion, performance on the generalization task in the three conditions differed from each other; generalization was most easy in the relevant change condition and more difficult if values of the irrelevant dimension changed. In the irrelevant change condition, we observed a direction toward the irrelevant dimension for some children because they consistently sorted cards according to the irrelevant sorting dimension (response probability of the low-performing state = .06). These results are in line with the idea that changes in the values of a dimension draw attention toward that dimension (Yerys & Munakata, 2006).

Table 2
Fit indexes of the four latent Markov models for the trial-by-trial data of the generalization phase of the generalization task for the three conditions separately.

Model	Log(L)	df	AIC	BIC	Δ Log(L)	Δ df	p [Δ Log(L)]
Relevant change condition							
One state[a]	−38.09	1	78.18	82.03			
Two states with two transitions	−37.17	5	84.34	103.60			
Two states with one transition	−37.91	4	83.81	99.22			
Two states without transitions	−37.34	3	80.68	92.24			
Irrelevant change condition							
One state	−135.04	1	272.08	275.92			
Two states with two transitions[a]	−74.72	5	159.43	178.61			
Two states with one transition	−77.52	4	163.04	178.38	5.60	1	<.05
Two states without transitions	−77.52	3	161.04	172.54	5.60	1	1
Total change condition							
One state	−84.61	1	171.22	174.97			
Two states with two transitions	−61.08	5	132.17	150.88			
Two states with one transition[a]	−61.11	4	130.22	145.19	0.05	1	.82
Two states without transitions	−63.64	3	133.27	144.50	5.06	1	<.05

Note: Log(L), log-likelihood; *df*, degrees of freedom; AIC, Akaike information criterion; BIC, Bayesian information criterion; Δ Log(L), log-likelihood ratio test; Δ *df*, difference in degrees of freedom in log-likelihood ratio test; *p* [Δ Log(L)], *p* value of log-likelihood ratio test.
[a] Preferred model.

Table 3
Fit indexes of the multi-group latent Markov models for the trial-by-trial data of the generalization task.

Model	Log(L)	df	AIC	BIC	Δ Log(L)	Δ df	p [Δ Log(L)]
Unequal response probabilities in both latent states	−176.44	10	372.88	421.98			
Equal response probabilities in latent state with a high response probability but unequal response probabilities in latent state with a low response probability[a]	−174.61	8	365.23	404.50	3.66	2	1
Equal response probabilities in both latent states	−177.16	7	368.33	402.69	5.10	1	<.05

Note: Log(L), log-likelihood; *df*, degrees of freedom; AIC, Akaike information criterion; BIC, Bayesian information criterion; Δ Log(L), log-likelihood ratio test; Δ *df*, difference in degrees of freedom in log-likelihood ratio test; *p* [Δ Log(L)], *p* value of log-likelihood ratio test.
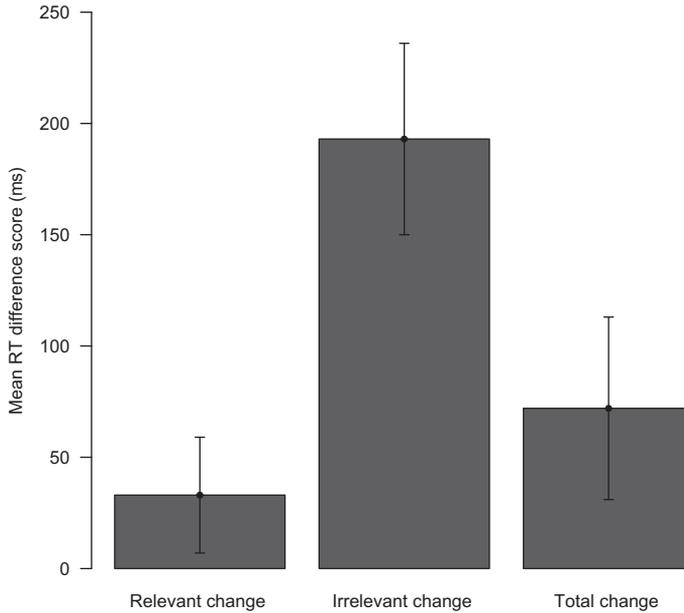[a] Preferred model.
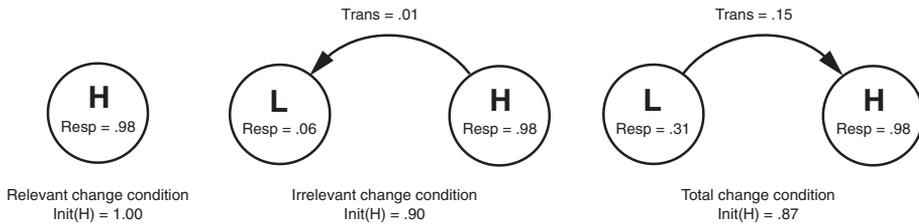
Fig. 3. Graphical representation of the optimal multi-group latent Markov model based on the trial-by-trial data of the generalization phase of the generalization task. Circles denote the latent states. Arrows between the circles denote transitions between the latent states. L, latent state with a low response probability; H, latent state with a high response probability; Resp, response probability; Trans, transition probability; Init(H), initial probability of the state with a high response probability.

Analyses of the reaction time (RT) difference scores (RT first generalization trial minus RT last baseline trial) of the generalization task confirmed the results of the analyses of the accuracy scores of this task. There was a significant difference between the RT difference scores in the three conditions, $F(2, 164) = 5.18$, $p < .01$, $r = .24$. Children in the relevant change condition had a smaller RT difference score than children in the irrelevant change condition, $F(1, 113) = 10.20$, $p < .01$, $r = .29$. Fig. 4 shows the mean RT difference scores in the three conditions.

DCCS task

In the post-switch phase of the DCCS task, most of the children responded correctly on zero or one (26%), or five or six (54%), of the six post-switch trials. We replicated earlier findings (van Bers et al., 2011) that a latent Markov model with two latent states with reciprocal transitions between these two states was the best fitting model. A graphical representation of the optimal latent Markov model is shown in Fig. 5, which also shows the parameter estimates. The optimal latent Markov model described above provides a characterization of the entire group of children who were tested. A posteriori, based on the optimal model, we determined for individual children whether they were switchers, perseverators, or in transition (see Visser, 2011). For any given response pattern, we computed the probability that the pattern was generated from only one state (either the switch state or the perseveration state) or from transitioning between the two states (i.e., posterior probabilities). All children were assigned to the group with their highest posterior probability, resulting in 103 children (62%) classified into the group of switchers, 42 children (25%) classified into the group of perseverators, and 22 children (13%) classified into the group of children in transition. There was a significant difference in age among the three groups of children, $F(2, 164) = 9.40$, $p < .01$, $r = .32$. Children who were classified as perseverators ($M_{age} = 44.9$ months, $SD = 5.9$) were significantly younger than children who were classified as switchers ($M_{age} = 49.6$ months, $SD = 6.5$), $F(1, 143) = 17.01$, $p < .01$, $r = .33$. The age of children who were classified as in transition ($M_{age} = 46.9$ months, $SD = 5.1$) was found to lie in between the ages of the other two groups.

Fig. 4. Mean reaction time (RT) difference scores (RT first generalization trial minus RT last baseline trial) in the three conditions. Error bars are standard errors of the mean.
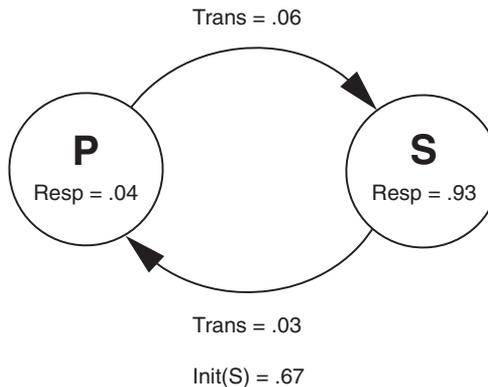
Fig. 5. Graphical representation of the optimal latent Markov model based on the trial-by-trial data of the post-switch phase of the DCCS task. Circles denote the latent states. Arrows between the circles denote a transition between the latent states. P, latent state with a low response probability (perseveration state); S, latent state with a high response probability (switch state); Resp, response probability; Trans, transition probability; Init(S), initial probability of the switch state.

Relationship between DCCS task and generalization task

The number of children categorized as in transition on the DCCS task was very low. Taking these children as a separate group into the analyses would have caused power problems. Because performance on the generalization task of the children in transition matched performance of the perseverators better than performance of the switchers, we took the group of perseverators and the group of children in transition together in subsequent analyses to enlarge the group size. Table 1 shows the number of children passing the generalization phase of the generalization task in the three conditions for the switchers, perseverators, and children in transition on the DCCS task.

To study the relationship between performance on the DCCS task and performance on the generalization task, we compared performance on the generalization task in the three conditions for the children who successfully switched on the DCCS task and for the children who did not switch (perseverators and children in transition). To test the interaction between condition (relevant, irrelevant, or total) and group (switchers or non-switchers), we conducted a logistic regression analysis with generalization performance as a (nominal) dependent variable (pass or fail), an intercept, and condition (2) and group (2) as (nominal) predictor variables. Performance in the relevant change condition did not differ for the two groups because all switchers and non-switchers passed the generalization phase in that condition, and this introduces an empty cell in the analysis. Therefore, we left this condition out of the analysis. There was a marginal main effect of condition ($\beta = -1.40$, Wald = -1.90, $p = .05$). There was no main effect of group, but there was an interaction between condition and group ($\beta = 2.59$, Wald = 2.11, $p < .03$). The switchers generalized relatively worst in the irrelevant change condition, whereas the non-switchers performed relatively worst in the total change condition.

Analyzing the two groups separately showed that performance on the generalization task in the three conditions differed significantly for the switchers, $\chi^2(df = 2, n = 103) = 11.81$, $p < .05$, and for the non-switchers, $\chi^2(df = 2, n = 64) = 5.64$, $p < .05$. For the switchers, more children in the relevant change condition passed the generalization phase than in the irrelevant change condition, $\chi^2(df = 1, n = 65) = 10.01$, $p < .05$. For the non-switchers, more children in the relevant change condition passed the generalization phase than in the total change condition, $\chi^2(df = 1, n = 38) = 5.58$, $p < .05$. In conclusion, children who switched on the DCCS task performed worst on the generalization task only if the values of the irrelevant sorting dimension changed, whereas non-switchers performed worst on the generalization task if the values of both the relevant and irrelevant sorting dimensions changed.

Discussion

We studied preschoolers' representations of sorting rules in the pre-switch phase of the DCCS task, where the rules were told and demonstrated. The study was set up to distinguish among three levels of abstraction: a representation at the level of the specific stimuli ("red car goes with red rabbit and blue rabbit goes with blue car"), a representation at the level of the values of dimensions ("red goes with red and blue goes with blue"), and a representation at the level of dimensions ("same colors go together"). All children who learned to execute sorting rules in the baseline phase showed very high performance on the generalization task in the relevant change condition (100%), suggesting an abstract rule representation at the level of dimensions for all of these children. A representation at the level of the values of dimensions or at the level of the specific stimuli would have resulted in low performance in this condition. Hence, we conclude that children with high and low cognitive flexibility do not differ in how they represent the pre-switch sorting rules. Therefore, the difference in performance on the DCCS task between these two groups seems to result from the processes that operate on the learned sorting rules (e.g., inhibition, reactivation, redescription, reflection) and not from the abstractness of the rule representations children have.

Nevertheless, we did find differences in performance between conditions on the generalization task, that is, suboptimal responding in the irrelevant change condition and the total change condition. These differences cannot be explained by differences in rule representations. In the irrelevant change condition, we observed a switch toward the irrelevant dimension for some children. The latent Markov modeling showed that these children consistently sorted test cards according to the irrelevant sorting dimension (their probability of sorting an item to the relevant dimension is .06). These results are in line with the idea that changes in the values of a dimension draw attention toward that dimension (Yerys & Munakata, 2006). In the total change condition, performance was less consistent. The latent Markov modeling showed that a small group of children was less consistent in sorting test cards according to one of the two dimensions (their probability of sorting an item to the relevant dimension is .31). In the total change condition, the values of both the relevant dimension and the irrelevant dimension changed. This seemed to distract some children from the relevant sorting dimension without sorting consistently according to the irrelevant sorting dimension. Performance in the irrelevant change condition and the total change condition of the generalization task was related to DCCS

performance. Switchers on the DCCS task generalized worst when only the values of the irrelevant dimension changed, whereas non-switchers on the DCCS task generalized worst when the values of both dimensions changed.

Endogenous and exogenous factors

The theory of endogenous and exogenous factors influencing sustained attention sheds light on these results. In the literature, different factors that influence preschoolers' performance on selection tasks, such as classification tasks, have been described. These factors have been described as exogenous (stimulus driven, bottom-up) or endogenous (expectancy driven, goal directed, top-down). Endogenous factors are thought to become more important over the course of development (Fisher, Thiessen, Godwin, Kloos, & Dickerson, 2013; Smith & Yu, 2013; Snyder & Munakata, 2010).

In the post-switch phase of the standard DCCS task, two factors are at play. The first factor is formed by the post-switch relevant sorting rules that the experimenter repeats verbally before each trial and that need to be kept in working memory. This factor is under voluntary control of children; therefore, we call it the *endogenous rule factor*. The second factor is formed by the pre-switch relevant sorting rules that are automatized by sorting according to these rules several times. This factor is not under voluntary control of the children; therefore, we call it the *automatic rule factor*. In our generalization task and the change versions of the DCCS task, an additional third factor is at play. This third factor is the *stimulus factor;* changes in the values of dimensions introduce stimulus novelty. This factor is stimulus-driven; therefore, it is exogenous (cf. Fisher et al., 2013). The endogenous rule factor in the generalization phase of our generalization task was learned by instruction in the baseline phase of the task. The rules were not repeated before every trial by the experimenter in the generalization phase anymore, but they might still have been active in working memory. The automatic rule factor in the generalization task is formed by the baseline sorting rules, which were automatized by sorting according to these rules several times. In the generalization task, the endogenous and automatic rule factor are expected to always direct attention in the same direction.

In the relevant change condition of the generalization task, the endogenous rule factor, the stimulus factor, and the automatic rule factor work together in directing the attention of children to the relevant sorting dimension. Performance was very high for all children in this condition. In the similar partial change version of the DCCS task (the values of the post-switch relevant sorting dimension change), the stimulus factor works together with the endogenous rule factor and against the automatic rule factor by directing the attention of children toward the post-switch relevant sorting dimension. This is consistent with previous results showing a trend for better performance on the partial change version compared with the standard DCCS task (Zelazo et al., 2003).

In the irrelevant change condition of the generalization task, the stimulus factor works against the endogenous rule factor and the automatic rule factor in directing the attention of children toward the irrelevant sorting dimension. For the switchers on the DCCS task, the irrelevant change condition of the generalization task was relatively most difficult. Because endogenous factors are thought to become more important over the course of development (Fisher et al., 2013; Smith & Yu, 2013; Snyder & Munakata, 2010), the most plausible explanation is a relatively weaker automatic rule factor (with regard to other factors) for switchers compared with non-switchers. This could be caused by stronger inhibition of the automatic rule factor by switchers, as assumed by the attentional inertia account (Kirkham et al., 2003). In the similar negative priming version of the DCCS task (the values of the post-switch irrelevant dimension change), the stimulus factor works together with the automatic rule factor and against the endogenous rule factor in directing the attention toward the post-switch irrelevant sorting dimension. This is consistent with previous results showing a trend for worse performance on the negative priming version compared with the standard DCCS task (Zelazo et al., 2003), affecting the switchers in a similar way as in the generalization task.

In the total change condition of the generalization task, the stimulus factor works both together with the endogenous rule factor and the automatic rule factor and against them, following the reasoning above. Non-switchers on the DCCS task performed worst on the total change condition of the generalization task. Apparently the non-switchers, in contrast to the switchers, were not directed in a specific direction but were occasionally distracted from the relevant sorting dimension by the

stimulus factor. In the similar total change version of the DCCS task (the values of both the post-switch relevant and post-switch irrelevant sorting dimension changes), the stimulus factor might be relatively strongest for the perseverators. Previous results showed that children performed better on the total change version than on the standard DCCS task (Zelazo et al., 2003), affecting the perseverators in a similar way as in the generalization task.

The results of the current study necessitate a new interpretation of the DCCS change studies of Zelazo et al. (2003). All children who learned the rule by receiving verbal instruction and demonstration seem to have the same abstract rule representation but differ in the way they are influenced by irrelevant and relevant changes in the task.

Competing memory systems account

The competing memory systems account (Morton & Munakata, 2002; Munakata, 1998) fits very well with the theoretical idea of competing endogenous and automatic rule factors presented before. According to this account, flexible behavior depends on the competition between active and latent memory traces. Perseveration occurs when an active memory trace of the post-switch relevant sorting rule is not strong enough to compete against a latent memory trace of the pre-switch relevant sorting rule. The competing memory systems account hypothesizes that there is a fundamental difference in rule representations between switchers and perseverators (Cohen & Servan-Schreiber, 1992; Kharitonova & Munakata, 2011; Kharitonova et al., 2009; Morton & Munakata, 2002). The active memory traces of switchers are thought to rely on later developing prefrontal cortical regions that represent the sorting rules in a more abstract form, whereas the latent memory traces of perseverators are thought to rely more on earlier developing posterior cortical regions that represent the sorting rules in a more stimulus-specific form. Although the results of the current study and the hypothesis of the competing memory systems account about fundamental differences in rule representations between switchers and perseverators seem to conflict, we think that they complement each other quite well.

In the current study, we investigated the abstractness of rule representations in the pre-switch phase of the DCCS task. Two factors are at play in the pre-switch phase. The first factor is an endogenous rule factor formed by the pre-switch (or baseline) sorting rules that the experimenter repeats verbally before every trial and that are kept in working memory. Hence, the endogenous factor is formed by the active memory traces. The second factor is an automatic rule factor that is formed by sorting repeatedly to the same pre-switch (or baseline) relevant sorting rules. Hence, the automatic rule factor is formed by the latent memory traces. When we asked children to generalize their sorting rules to novel stimuli after the baseline phase, both switchers and perseverators could use the endogenous rule factor because it was not in conflict with the automatic rule factor. It is important to note that the latent memory does not suggest alternative sorting behavior during generalization. Hence, both perseverators and switchers use abstract representations to generalize the pre-switch sorting rules (as was found in the current study).

The situation is different for generalization of the post-switch sorting rules. Two factors are at play in the post-switch phase of a standard DCCS task. The first factor is an endogenous rule factor formed by the post-switch relevant sorting rules that the experimenter repeats verbally before each trial and that depends on active memory. The second factor is an automatic rule factor that is formed by repeatedly sorting in the pre-switch phase and that depends on latent memory. When asking children to generalize their sorting rules to novel stimuli after the post-switch phase (as in Hanania, 2010, and Kharitonova et al., 2009), perseverators based their behavior on the automatic rule factor (representing the pre-switch relevant sorting rules), whereas switchers based their behavior on the endogenous rule factor (representing the post-switch relevant sorting rules). This would explain fundamentally different generalization behavior for switchers and perseverators after the post-switch phase.

Our results do not necessarily conflict with the conclusions of Kharitonova and Munakata (2011) about the specific relation between abstraction and flexibility as measured following the DCCS pre-switch phase. It seems that the tests of abstraction designed by Kharitonova and Munakata (2011) concern the ability to form abstract rules from examples. This contrasts with our generalization test because the latter tests the abstractness of rules that were learned by instruction, and this likely involves different processes. Although the precise relation between these two aspects of abstractness

is not immediately clear, results are not necessarily conflicting. From adult literature, it is known that different types of learning processes involve different brain areas even with the same stimuli and category structure (e.g., Shohamy et al., 2004).

In conclusion, the competing memory systems account gives a good explanation for the finding that perseverators use abstract representations under some conditions (when active memory is not in conflict with latent memory) but use stimulus-specific representations under other conditions (when active memory is in conflict with latent memory).

The interpretation of our results in terms of the competing memory systems accounts yields some suggestions for future studies. First, the relation between the generalization task and the DCCS task is now established by two sorting tasks that depend on the same stimulus dimensions. It is predicted that the same results hold if the two tasks do not share stimulus dimensions, for example, color and shape in the DCCS task and orientation or patterns in the generalization task (cf. Kharitonova & Munakata, 2011). Second, it is predicted that a generalization task, as we designed in the current study, following the post-switch phase would result in different performance for switchers and perseverators. Switchers would show similar behavior as in the current study, relying on active memory. Perseverators, however, are expected to generalize their pre-switch sorting rules (which are their sorting rules in the post-switch phase) in the irrelevant and relevant change condition. In the total change condition, they might finally switch to the post-switch sorting rules.

Conclusion

Based on our results, we can conclude that there is no difference in the abstractness of rule representations in the pre-switch phase of the DCCS task between children with high cognitive flexibility and children with low cognitive flexibility. All children who learned the rules by receiving verbal instruction and demonstration seem to have an abstract rule representation at the level of dimensions. Therefore, the difference in performance on the DCCS task between switchers and perseverators seems to result from the processes that operate on the learned sorting rules (e.g., inhibition, reactivation, redescription, reflection) and not from the abstractness of the rule representations children have. However, performance of switchers and perseverators seems to be differentially vulnerable to changing stimulus features, that is, exogenous factors. It is believed that endogenous factors become more important with development (Fisher et al., 2013; Snyder & Munakata, 2010), implying that the influence of the automatic rule factor is relatively weaker for switchers. The current results for switchers in the irrelevant change condition of the generalization task suggest that the influence of the automatic rule factor, relative to other factors, decreases with age. This may be caused by stronger inhibition of the automatic rule factor by switchers, as assumed by the attentional inertia theory (Kirkham et al., 2003). Future studies need to confirm this hypothesis.

Acknowledgments

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