Dynamics, models, and mechanisms of the cognitive flexibility of preschoolers
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Citation for published version (APA):
van Bers, B. M. C. W. (2014). Dynamics, models, and mechanisms of the cognitive flexibility of preschoolers

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Download date: 16 Dec 2018
Preschoolers can form abstract rule representations regardless of cognitive flexibility

This chapter is based on:
Abstract
The abstractness of rule representations in the pre-switch phase of the Dimensional Change Card Sorting (DCCS) task is 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, which implies 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 if only values of the irrelevant dimension changed. Children with lower cognitive flexibility were more often inconsistent in their sorting on the generalization task if values of both dimensions changed. These findings support the view that DCCS perseverators suffer from attentional inertia at the level of dimensions and that differences between switchers and perseverators at the standard DCCS task are not due to differences in representations of sorting rules.

3.1 Introduction
Flexibility is an important ability in the present rapidly changing society. One should be able to change plans in response to relevant changes in the environment and complementary to maintain activities when changes in the environment are irrelevant. Cognitive flexibility is improving importantly 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 re-description account perseverators can conceptualize a stimulus in a single way, i.e. using the pre-switch rules, but fail to re-describe 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, while 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, & Koepppe, 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 (such as inhibition, reactivation, and re-description).

Reprsentations 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 project is to study the abstractness of the pre-switch rule representations of children in the DCCS task. 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’. And 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, 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 present 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 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 et al. assumed a link between active representations that support switching and abstract representations that support generalization. In another study, Kharitonova and Munakata (2011) showed that this possible link between flexibility and abstraction is general across dimensions and ordering of the two tasks and that the link is specific to tasks that require the use of flexible and abstract representations. However, it is important to note that the generalization task Kharitonova et al., and Kharitonova and Munakata used in their studies 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 (thus 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). In addition to the application of abstract sorting rules children also have to make a similarity match. The sorting rules that would lead to successful performance in the generalization task of Kharitonova et al. and Kharitonova and Munakata 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.

Hanania (2010) also studied children’s representations of DCCS sorting rules 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 that perseverated in the post-switch phase of the DCCS task successfully switched when novel stimuli were presented, while 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 that perseverate at the level of dimensions (children who continued to sort according to the initial dimension in the additional third
phase) and children that 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, which made an abstract representation of the sorting rules at the level of dimensions unnecessary.

Zelazo et al. (2003) studied children’s representations of DCCS 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- 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 is relevant in the post-switch phase, changed. In the negative priming version only the values of the dimension that is relevant in the pre-switch phase, changed. Children performed better on the total change version than on the standard DCCS task, which 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% respectively in experiments 7, 8, and 9). 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, which 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, which makes it difficult to draw clear conclusions about the abstractness of the rule representations in the
DCCS task on the basis of these studies.

**Current Project**

Previous studies into the relationship between abstraction ability and DCCS performance have either administered the generalization task after the post-switch phase of the task, have had additional task demands, or used indirect measures. The goal of the current study is to directly assess the abstractness of children’s rule representations in the pre-switch phase of the DCCS task. This research question is studied by asking children to generalize their 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 study the relationship between the representation of the pre-switch sorting rules and the ability to switch. The generalization task resembles the DCCS task as much as possible and consists of two phases. The first phase of the generalization task (the base-line phase) is 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 base-line phase need to be generalized to test and target-cards with changed values on one or both dimensions.

In order 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 have to sort according to color in the base-line 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 have to sort according to color in the base-line phase, the shapes of the test- and target cards change. In the total change condition the values of both dimensions change. If children have to sort according to color in the base-line 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 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 between conditions even in the case that the abstractness of the rule representations is equal for all children: changes in the values of one dimension would draw attention towards this dimension. Changes in the dimension that is irrelevant in the pre-switch phase of the DCCS task would draw attention to this dimension, which makes switching easier because that dimension is relevant in the post-switch phase. In the generalization task children do not have to make a switch but have 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 would changes in the irrelevant sorting dimension, 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 study the possible relationship between abstraction and flexibility by relating performance on the generalization task and performance on a standard DCCS task.

3.2 Method
Participants
A total of 167 children participated in this study: 77 3-year-olds ($M = 42.0$ months, $SD = 3.1$, range = 36 - 47, 41 boys and 36 girls), and 90 4-year-olds ($M = 53.2$ 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 ($n = 11$), 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 \((n = 58, M = 48.1 \text{ months}, SD = 6.5, \text{ range} = 36 - 59, 30 \text{ boys and 28 girls})\), the *irrelevant change* condition \((n = 57, M = 48.0 \text{ months}, SD = 6.2, \text{ range} = 36 - 59, 31 \text{ boys and 26 girls})\), or the *total change* condition \((n = 52, M = 48.1 \text{ months}, SD = 6.9, \text{ range} = 36 - 59, 25 \text{ boys and 27 girls})\). 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 the three conditions. However, there was a difference between the generalization tasks in the three conditions. In the relevant change condition, the values of the sorting dimension that is relevant change in the generalization task. In the irrelevant change condition the values of the irrelevant dimension change. In the total change condition the values of both the relevant and irrelevant dimension change. If children sorted to color in the generalization task, they switched from sorting to color to sorting to shape in the DCCS task. If children sorted to shape in the generalization task, they switched from sorting to shape to sorting 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 x 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 grey background \((1024 \times 768 \text{ pixels})\). In both tasks two light grey sorting stacks \((220 \times 270 \text{ pixels})\) were presented in the bottom left and right corner of the screen. Above them, the target cards \((200 \times 163 \text{ pixels})\) were depicted. A test card \((270 \times 220 \text{ pixels})\) 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 Figure 3.1 for an example of the computer screen.

![Figure 3.1](image)

**Figure 3.1**  Example of the computer screen with target cards, target stacks, and test cards.

Two sets of cards were used. Cards in set A depicted stimuli with the shapes and colors: rabbit, chicken, pig, fish, green, yellow, orange and purple. Cards in set B depicted stimuli with the 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 base-line 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 base-line 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. If a child, for example, sorted yellow rabbits and green chickens to color in the base-line 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 to color in the base-line 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 dimension changed.
If a child sorted yellow rabbits and green chickens to color in the base-line 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 Figure 3.2 for examples of target- and test cards used in the generalization- and DCCS task in the three conditions.

**Generalization task**

<table>
<thead>
<tr>
<th>Condition</th>
<th>Base-line phase (color)</th>
<th>Generalization phase (color)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relevant change</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Target cards</td>
<td><img src="image1" alt="Target cards" /></td>
<td><img src="image2" alt="Target cards" /></td>
</tr>
<tr>
<td>Test cards</td>
<td><img src="image3" alt="Test cards" /></td>
<td><img src="image4" alt="Test cards" /></td>
</tr>
<tr>
<td>Irrelevant change</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Target cards</td>
<td><img src="image5" alt="Target cards" /></td>
<td><img src="image6" alt="Target cards" /></td>
</tr>
<tr>
<td>Test cards</td>
<td><img src="image7" alt="Test cards" /></td>
<td><img src="image8" alt="Test cards" /></td>
</tr>
<tr>
<td>Total change</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Target cards</td>
<td><img src="image9" alt="Target cards" /></td>
<td><img src="image10" alt="Target cards" /></td>
</tr>
<tr>
<td>Test cards</td>
<td><img src="image11" alt="Test cards" /></td>
<td><img src="image12" alt="Test cards" /></td>
</tr>
</tbody>
</table>
**Figure 3.2** Examples of target cards and test cards used during the different phases of the generalization task and the DCCS task 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 base-line 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 base-line phase. The child was then asked to sort six test cards him- 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 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 had to sort at least five of the six test cards correctly to pass the base-line 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 base-line phase, children were not given feedback on their sorting in the generalization phase.

After a break of approximately five minutes, during which the experimenter and the child read a book, the second task was administered. The experimenter explained the rules of the new game (sorting to color or sorting 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 exact the same way as the base-line 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 had 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 exact 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 was counterbalanced.

Statistical approach

In order 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 project is fitting latent Markov models (Rabiner, 1989; Van de 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 expect 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, Chapter 2) showed that fitting latent Markov models is a reliable statistical method to classify post-switch DCCS data into latent subgroups. We will use 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 can 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.

To the trial-by-trial data of the generalization phase of the generalization task we fitted several latent Markov models: 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 between the three conditions. This way we could test for possible differences between the three conditions.

To the trial-by-trial data of the post-switch phase of the DCCS task we also fitted several latent Markov models: 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, Chapter 2).

Models were fit to the data by calculating maximum likelihood estimates of the parameters. We used model selection methods (information criteria, log-likelihood difference tests) to determine which model described the trial-by-trial data of the post-switch phase of the DCCS task and of the generalization phase of the generalization task best. Hypotheses concerning the number of latent states in the latent Markov models were tested with two commonly used information criteria, AIC (Akaike, 1974) and BIC (Schwarz, 1978). Lower AICs or BICs indicate 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 is significant, the
null hypothesis of equal model fit is rejected, and the less parsimonious model is preferred. Otherwise the more parsimonious model is preferred.

3.3 Results

No significant effects were found for gender, order of the two sets of cards, or order of the two sorting dimensions. Therefore, all results are collapsed across those variables. No significant effects were found for the order of the two tasks either. There is no significant difference in the percentage of children passing the generalization phase of the generalization task between the children that performed the generalization task first and the children that performed the DCCS task first in the relevant change condition (100% of the children pass), in the irrelevant change condition, $\chi^2(df = 1, n = 57) = .004, p = .95$, or in the total change condition, $\chi^2(df = 1, n = 52) = .59, p = .42$. There is also no significant difference in the distribution of the number of switchers, perseverators and children in transition between the children that performed the generalization task first and the children that performed the DCCS task first, $\chi^2(df = 2, N = 167) = 3.34, p = .19$. Which means that there is no difference in performance on the switch task between the children that performed the generalization task first and the children that performed the DCCS task first. Therefore, results are collapsed across this variable as well.

Representation of 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. Almost 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 form a representation at the level of dimensions, i.e. “same colors go together”, because all children successfully generalize in the relevant change condition. Hence, possible differences between conditions
cannot be explained by the abstractness of sorting rules.

Differences between conditions on the 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 to the base-line sorting rules were considered to have passed the generalization phase. Table 3.1 shows the number of children passing the generalization phase in the three conditions. All of the 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 between the three conditions, \( \chi^2(\text{df} = 2, N = 167) = 10.55, p < .01 \). Planned comparisons revealed that more children passed the generalization phase in the relevant change condition than in the irrelevant change condition, \( \chi^2(\text{df} = 1, n = 115) = 11.15, p < .01 \), and in the total change condition, \( \chi^2(\text{df} = 1, n = 110) = 7.08, p < .01 \).

Table 3.1  Number of children passing the generalization phase of the generalization task in the three conditions for the children categorized as perseverators, in transition or switchers.

<table>
<thead>
<tr>
<th>Group</th>
<th>Relevant change condition</th>
<th>Irrelevant change condition</th>
<th>Total change condition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>pass</td>
<td>fail</td>
<td>pass</td>
</tr>
<tr>
<td>Perseverators n = 42</td>
<td>18 (100%)</td>
<td>0 (0%)</td>
<td>13 (93%)</td>
</tr>
<tr>
<td>In transition n = 22</td>
<td>6 (100%)</td>
<td>0 (0%)</td>
<td>11 (92%)</td>
</tr>
<tr>
<td>Switchers n = 103</td>
<td>34 (100%)</td>
<td>0 (0%)</td>
<td>23 (74%)</td>
</tr>
<tr>
<td>Total N = 167</td>
<td>58 (100%)</td>
<td>0 (0%)</td>
<td>47 (82%)</td>
</tr>
</tbody>
</table>

Note. In each column left the number of children passing the generalization phase in that condition and right the number of children failing the generalization phase.
phase in that condition. Children who sorted at least five of the six generalization trials according to the base-line sorting rules were considered to have passed the generalization phase.

Model-based analyses

In order 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 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 3.2 shows the fit indices of the different models in the three conditions. In the relevant change condition, the model with one state fits the data better than the models with two states (compare AIC and BIC in the upper section of Table 3.2). In the irrelevant change condition, the models with two latent states fit the data better than the model with one latent state (see middle section of Table 3.2). The full model with two latent states and bi-directional transitions between the two latent states fits the data best and was preferred, although the differences in fit between the three models with two states were very small. In the total change condition, the models with two latent states fit the data better than the model with one latent state (see lower section of Table 3.2). The two-state model with only one transition (from the low performing group to the high performing group) fits the data best and was preferred.
Table 3.2  Fit indices 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.

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

Note. Log(L) = Log-likelihood, df = degrees of freedom, AIC and BIC = information criteria, 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. * indicates preferred model.
In order to test whether the response probabilities for the two latent states of the three preferred models differed between 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 3.3). 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 Figure 3.3, which also shows the parameter estimates. In conclusion performance on the generalization task in the three conditions differs 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 towards 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 towards that dimension (Yerys & Munakata, 2006).
Table 3.3  
Fit indices of the multi-group latent Markov models for the trial-by-trial data of the generalization task

<table>
<thead>
<tr>
<th>Model</th>
<th>Log (L)</th>
<th>df</th>
<th>AIC</th>
<th>BIC</th>
<th>∆ Log (L)</th>
<th>∆ df</th>
<th>p (∆ Log (L))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unequal response probabilities in both latent states</td>
<td>-176.44</td>
<td>10</td>
<td>372.88</td>
<td>421.98</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equal response probabilities in latent state with a high response probability but unequal response probabilities in latent state with a low response probability*</td>
<td>-174.61</td>
<td>8</td>
<td>365.23</td>
<td>404.50</td>
<td>3.66</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Equal response probabilities in both latent states</td>
<td>-177.16</td>
<td>7</td>
<td>368.33</td>
<td>402.69</td>
<td>5.10</td>
<td>1</td>
<td>&lt; .05</td>
</tr>
</tbody>
</table>

Note. Log(L) = Log-likelihood, df = degrees of freedom, AIC and BIC = information criteria, ∆ Log (L) = Log-likelihood ratio test, ∆ df = difference in degrees of freedom in Log-likelihood ratio test, p (∆ Log (L)) = p-value of Log-likelihood ratio test. * indicates the preferred model.

Figure 3.3  
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 base-line trial) of the generalization task confirms the results of the analyses of the accuracy scores of this task. There is a significant difference between the RT difference scores in the three conditions, $F(2,164) = 5.18$, $p < .01$. Children in the relevant change condition have a smaller RT difference score than children in the irrelevant change condition, $F(1,113) = 10.20$, $p < .01$. Figure 3.4 shows the mean RT difference scores in the three conditions.

![Figure 3.4](image)

**Figure 3.4** Mean Reaction Time (RT) difference score (RT first generalization trial minus RT last base-line trial) in the three conditions. Error bars are standard errors of the mean.

**DCCS task**
In the post-switch phase of the DCCS task most of the children either 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, Chapter 2) 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 Figure 3.5, which also shows the parameter estimates. The optimal latent Markov model described above provides a characterization of the entire group of children that was tested. A posteriori, based on the optimal model, we determined for individual children whether they were switchers, perseverators, or whether they were in transition (see Visser, 2011). For any given response pattern, we computed the probability that that 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 between the three groups of children, $F(2,164) = 9.40, p < .01$. Children that were classified as perseverators ($M = 44.9$ months, $SD = 5.9$) were significantly younger than children that were classified as switchers ($M = 49.6, SD = 6.5$), $F(1,143) = 17.01, p < .01$. The age of children that were classified as in transition ($M = 46.9, SD = 5.1$) was found to lie in between the ages of the other two groups.

![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.](image-url)

**Figure 3.5**

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), $\text{Resp} =$ response probability, $\text{Trans} =$ transition probability, $\text{Init} (S) =$ 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 is very low. Taking these children as a separate group into the analyses would cause power problems. Because performance on the generalization task of the children in transition matches performance of the perseverators better than performance of the switchers, we have taken 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.

In order 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, total) and group (switchers, non-switchers) we conducted a logistic regression analysis with generalization performance as (nominal) dependent variable (pass, 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, which introduces an empty cell in the analysis. Therefore, we left this condition out of the analysis. There was a marginal main effect of condition, \( \text{Beta} = -1.40, \text{Wald} = -1.90, p = .05 \). There was no main effect of group, but there was an interaction between condition and group, \( \text{Beta} = 2.59, \text{Wald} = 2.11, p < .03 \). 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 shows 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 if only 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 dimension changed.

### 3.4 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 between 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’). Very high performance of all children (100%) on the generalization task in the relevant change condition suggests an abstract rule representation at the level of dimensions for all children who learned to execute sorting rules in the first phase. 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 sorting rules. Therefore, the difference in performance on the DCCS task between these two groups lies in the processes that operate on the learned sorting rules (such as inhibition, reactivation, or re-description), and not in 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 total change condition. These differences cannot be explained by differences in rule representations. In the irrelevant change condition we observed a switch towards the irrelevant dimension for some children. The latent Markov modeling shows 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). In the total change condition performance was less consistent. The latent Markov
modeling shows that a small group of children is 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). Performance in these conditions of the generalization task is 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.

In the literature, different factors have been described that influence preschoolers’ performance on selection tasks, such as classification tasks. 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; Snyder & Munakata, 2010; Smith & Yu, 2012).

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, which have to be kept in working memory. This factor is under voluntary control of the children, and we therefore call it the endogenous rule factor. The second factor is formed by the pre-switch relevant sorting rules, which are automatized by sorting to these rules several times. This factor is not under voluntary control of the children, and we therefore 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, and therefore exogenous (cf. Fisher et al., 2013). The endogenous rule factor in the generalization phase of our generalization task was learned by instruction in the base-line phase of the task. The rules are not repeated before every trial by the experimenter in the generalization phase anymore, but may still be active in working memory. The automatic rule factor in the generalization task is formed by the base-line sorting rules, which are automatized by sorting to these rules several times. In the generalization task the endogenous and automatic rule factor are expected to direct attention always 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 the child to the relevant sorting dimension. Performance is 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 the child towards the post-switch relevant sorting dimension. This is consistent with previous results showing a trend for better performance on the partial change version compared to 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 the child towards the irrelevant sorting dimension. For the Switchers on the DCCS task the irrelevant change condition of the generalization task was relatively most difficult. This can only be explained by a relatively weaker automatic rule factor (with regard to other factors) for switchers compared to non-switchers. The attentional inertia theory (Kirkham, Cruess & Diamond, 2003) gives a good explanation for these results, namely inhibiting or suppressing attention to the pre-switch relevant information. 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 by directing the attention towards the post-switch irrelevant sorting dimension. This is consistent with previous results showing a trend for worse performance on the negative priming version compared to 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 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 the post-switch irrelevant sorting dimension change) 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. (2013). All children seem to have the same abstract rule representation, but differ in the way they are influenced by irrelevant and relevant changes in the task. The competing memory systems account (Morton & Munakata, 2002) fits very well with the theoretical idea of competing endogenous and automatic rule factors presented before. However, the implementation of this framework conflicts with the current results. The competing memory systems account hypothesizes a fundamental difference in rule representations between switchers and perseverators (Cohen & Servan-Schreiber, 1992; Morton & Munakata, 2002). Whereas, the current results assume that rule representations are abstract in all cases.

Conclusion
Based on our results, we can conclude that there is no difference in the abstractness of rule representations in the DCCS task between children with high and low cognitive flexibility. All children who learned the rule by receiving verbal instruction and demonstration have an abstract rule representation at the level of dimensions. Differences in performance between switchers and perseverators on the DCCS task lie in the processes that operate on the learned sorting rules, such as inhibition, reactivation, and redescription. The most plausible explanation of perseverative behavior on the DCCS task, based on the current results with the generalization task, is attentional inertia at the level of dimensions (Kirkham, Cruess, and Diamond, 2003). Perseverators may know the new rules they should be following, but the automatic rule factor driving attention towards the old dimension is too strong. The influence of the automatic rule factor seems less strong for switchers. It is likely that endogenous factors become more important with development (Fisher et al., 2013; Snyder & Munakata, 2010). The current results for switchers in the irrelevant change condition of the generalization task suggests that the
influence of the automatic rule factor, relative to other factors, decreases with age, which needs to be confirmed in future studies.

**Acknowledgements**

We would like to thank participating children, parents, day-care centers and primary schools. Thanks to Iwris Kelly, Erica Neutel, Annemarie Oskam, Judith Pietersen, and Lillian Stolk for assisting with data collection.