Dynamics, models, and mechanisms of the cognitive flexibility of preschoolers

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The dynamics of development on the Dimensional Change Card Sorting task

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Abstract
A widely used paradigm to study cognitive flexibility in preschoolers is the Dimensional Change Card Sorting (DCCS) task. The developmental dynamics of DCCS performance was studied in a cross-sectional design (N = 93, 3- to 5 years of age) using a computerized version of the standard DCCS task. A model-based analysis of the data showed that development on the DCCS task is best described as a discontinuous change in performance on the post-switch phase of the task. In addition to a perseveration group and a switch group, a transitional group that showed shifts between perseverating and switching during the post-switch trials, could be distinguished. Computational models of performance and development on the DCCS task cannot, in their current forms, explain these results. We discuss how a catastrophe model of the developmental changes in task performance could be used to generate specific hypotheses about the variables that control development of DCCS performance.

2.1
Introduction

The ability to behave flexibly is a crucial aspect of human cognition and a significant ability in every day life. It allows one to break habits and to deal with novel situations. However, sometimes people are unable to act flexibly and instead perseverate, repeating old behaviors that are no longer appropriate (Diamond, 1985; Piaget, 1954). A widely used paradigm to study cognitive flexibility in preschoolers is the Dimensional Change Card Sorting (DCCS) task (Zelazo, 2006). In this task, children are shown two target cards that vary along two dimensions (e.g. color and shape), and they are asked to sort a series of bivalent test cards first according to one dimension (e.g. color), and then according to the other dimension (e.g. shape). Each test card matches one target card on one dimension and the other target card on the other dimension. In the pre-switch phase of the task, 3-year-olds have no problems sorting test cards according to shape or color. However, they do have problems in the post-switch phase of the task, when they have to switch sorting dimensions. Typically, 3-year-olds perseverate in the post-switch phase by sorting test cards according to the initial dimension, whereas most 5-year-olds switch immediately to the new dimension when asked to do so (Zelazo, 2006).

Different theoretical frameworks have been proposed to explain perseverative behavior on the DCCS task. The *cognitive complexity and control* theory postulates that switching dimensions on the DCCS task requires the formulation and use of a higher-order rule for selecting which pair of rules (color rules or shape rules) must be used on a particular trial, which is a problem for young children (Zelazo & Frye, 1997; See Ramscar, Dye, Witten and Klein, 2009 for a related interpretation). The *attentional inertia* theory assumes that children who perseverate in the post-switch phase of the DCCS task fail to suppress attention to the first dimension in order to shift attention to the second dimension (Kirkham, Cruess & Diamond, 2003). According to the *activation-deficit* hypothesis, inflexibility on the DCCS task is caused by a failure to activate previously ignored information (Chevalier & Blaye, 2008). Perner and Lang (2002) posit that children who perseverate find it difficult to *re-describe* the stimuli on the test cards according to a different dimension. Finally, the *competing memory systems* theory supposes that flexible behavior depends on the relative strength of latent and active memory traces (Munakata, 1998). According to this theory, perseveration occurs when an active memory trace of the currently relevant rules is insufficiently strong to compete against a latent memory trace of the previously relevant rules.

To explain the results of empirical studies, a number of computational models of behavior and development on the DCCS task have been proposed (Buss & Spencer, 2008; Morton & Munakata, 2002; Marcovitch & Zelazo, 2000). These computational models specify mechanisms underlying the development of flexible sorting behavior. In these models, developmental change is formalized in terms of one or more parameters of the model, such as the strength of working memory relative to the strength of long-term memory (Buss & Spencer, 2008; Morton & Munakata, 2002) or the impact of the length of training on performance (Marcovitch & Zelazo, 2000). Consequently, these models relate to cognitive and or neural systems in the brain that play a crucial role in the development of flexible behavior. Such models have been evaluated by comparing the behavior of models with two different parameter settings (a younger and an older model) with empirical data from children of different ages. Since these models are defined as dynamical systems, they also have implications for the process of change between a younger and an older model

(Van der Maas & Raijmakers, 2009). However, such implications have not been tested explicitly.

Dynamics of development

In addition to the computational models, it is also possible to formalize the dynamics of a developmental process without specifying a mechanism of change in terms of neural or cognitive systems. Formal mathematical models of developmental dynamics, such as catastrophe models (Thom, 1975; Van der Maas & Molenaar, 1992), could provide insight into the variables that control the developmental process, without making detailed assumptions about a possible mechanism, such as in computational models. In contrast to computational models, these formal models are descriptive models of the observed behavior. Nevertheless, these models may generate novel and testable predictions about performance on the task.

To reveal the dynamics of behavior from empirical data, statistical analyses should test whether the data can best be described in terms of multiple behavioral modes. Furthermore, the dynamics of the behavior should be expressed in terms of changes within and between behavioral modes. Latent Markov analysis (Rabiner, 1989; Van de Pol & Langeheine, 1990) and stochastic catastrophe theory (Wagenmakers, Molenaar, Grasman, Hartelman & Van der Maas, 2005) provide suitable statistical tests to contrast predictions from different dynamical models. The focus of the current project is to uncover important aspects of the dynamics of children's development on the DCCS task. That is, to study the developmental trajectory from perseverating to switching in the post-switch phase of this task.

Children's performance on the DCCS task often appears to be bimodal. That is, most children either sort none of the post-switch cards correctly or sort all post-switch cards correctly, but on closer examination some continuous variation is occurring. The bimodal distribution of the data would indicate two modes of behavior and raises the question whether development on the DCCS proceeds continuously or discontinuously. Continuous versus discontinuous change is a central and recurrent theme in developmental psychology (e.g. Brainerd, 1978; Fisher, Pipp & Bullock, 1984; Jansen & Van der Maas, 2001).

Based on the distribution of accuracy data of previous studies, the possible dynamical models for DCCS developmental change can be restricted to a few general cases: A continuous developmental model with a rapid acceleration, a step-wise developmental model, and a discontinuous developmental model as described by formal models of phase transitions (Thom, 1975; Van der Maas & Molenaar, 1992). According to the continuous developmental model, children use one strategy across all ages, but become gradually better in generating correct answers with age. In a step-wise developmental model children suddenly jump from one strategy to the other. Importantly, at each single moment during their development children exclusively use one strategy or the other, and once they have learned the correct strategy they stop using the incorrect strategy altogether. According to a discontinuous developmental model children also make a sudden jump from one strategy to the other. However, there is a transitional period during which children have both strategies at their disposal and can use both of them within a short period of time (Van der Maas & Molenaar, 1992). We will test these three hypotheses about the dynamics of development in empirical data.

Current approach

Standard analyses of DCCS task data use sum-scores of the post-switch trials. For the continuous and step-wise developmental models, sum-scores contain all the information that is necessary to describe development. According to these models, children use one strategy at a certain time point and, given this strategy, the probability of a correct response is the same on all post-switch trials. But according to the discontinuous developmental model, children in transition may use both strategies over a short period of time and therefore, the probability of a correct response can change over the course of the post-switch trials. In order to distinguish between the different developmental models of performance on the DCCS task, we modeled trial-by-trial behavioral data of the post-switch phase of the task with latent Markov models (Rabiner, 1989; Van de Pol & Langeheine, 1990). In latent Markov models, one or more latent states are defined which are associated with a prototypical pattern of responding. By comparing the goodness-of-fit of different models that are consistent with different developmental trajectories, we can infer key aspects of the dynamics of development on the DCCS task.

Catastrophe theory offers additional tests of discontinuous development through so-called catastrophe flags, such as *critical slowing down, sudden jumps, hysteresis,* and *divergence*. Catastrophe flags are typical properties of behavior that indicate, and sometimes predict the occurrence of a discontinuous transition (Gilmore, 1981; Scheffer et al., 2009; Van der Maas & Molenaar, 1992). If one of these flags is observed one expects the others also to occur in case of a genuine transitional process. Hence, indication of several flags together in the empirical data makes a strong point for genuine discontinuous transitions in development. The catastrophe flag critical slowing down means a delayed recovery of stability after perturbation in the transition phase. It is a necessary but not sufficient property of a system undergoing a discontinuous transition. Reaction times can be used to test for this flag in children's performance on post-switch trials of the DCCS task (Van der Maas, Raijmakers, Hartelman & Molenaar, 1999). Reaction times to the post-switch trials for children in transition are expected to be slower than reaction times of children consistently perseverating or switching. There is already some empirical indication that children in transition respond slower than children consistently perseverating or switching. Diamond, Carlson and Beck (2005) showed that, in particular, the oldest children who cannot switch and the youngest children who can switch show hesitations. Hesitations were signs of indecision, such as moving first towards one tray and then the other. This behavior suggests relatively long reaction times for children in transition.

The main goal of this paper is to study the dynamics of children's development on the DCCS task without making specific assumptions about the underlying variables that control the developmental process or the theoretical models on which they are based. Nevertheless the results of our analyses do have consequences for the computational models proposed in literature that explain behavior and development on the DCCS task. The implications of our results for the specific computational models are elaborated in the discussion. Finally we discuss how a substantive interpretation of a dynamical model that incorporates our findings could be used to test specific hypotheses about the variables that control development of DCCS performance.

2.2
Method

Participants

A total of 93 children participated in this study: 43 3-year-olds (M = 42.4 months, SD = 3.3, range = 36 – 47, 22 girls), 27 4-year-olds (M = 53.7 months, SD = 3.7, range = 48 – 59, 14 girls), and 23 5-year-olds (M = 66.9 months, SD = 2.7, range = 62 – 71, 12 girls). We tested another 15 children but their data could not be used because they did not pass the training phase (n = 1), did not pass the pre-switch phase (n = 5), refused to complete testing (n = 4), or due to experimenter error (n = 5). Children were recruited from three day-care centers and one primary school in the Netherlands. Informed consent was obtained from the parents of all children who participated.

Design

Each child was tested on two versions of the task. The standard version with stimuli that depicted colored shapes with black outlines on a white background and a separated dimensions version with stimuli that depicted colorless shapes with black outlines on a colored background. Only the results of the standard version are reported in this paper. Two sets of shapes and colors were used in both versions. The order of presentation of the two versions, the order of the sets of shapes and colors, and the order of the two sorting dimensions (color and shape) were counterbalanced and crossed within each age x gender cell.

Materials

The experiment was conducted using a laptop computer with a touch-screen monitor. The task was programmed using the software package Authorware version 7.0. Stimuli were presented against a dark grey background (1024 x 768 pixels). Two light grey sorting stacks (270 x 220 pixels) were present in the bottom left and right corner of the screen. Above them, the target cards (200 x 163 pixels) were depicted. A test card (270 x 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. Two sets of colors and shapes were used. Set A consisted of the shapes and colors: cat, boat, flower, green, yellow and purple. Set B consisted of the shapes and colors: bear, car, house, red, blue and orange. If a child performed the task with target cards that depicted a green cat and a yellow boat, the two test cards depicted a yellow cat and a green boat. Each test card matched one target card on one dimension and the other target card on the other dimension. Therefore, the correct answer when sorting by color was the wrong answer when sorting by shape. In this example, the child was trained to sort by color with two training cards and target cards that depicted a green or a yellow flower. And he or she was trained to sort by shape with two training cards and target cards that depicted a purple cat and a purple boat.

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 by showing and by allowing children to sort example cards that were not related to the task. No target cards were visible during this warm-up phase. After the child demonstrated that he or she could sort cards, the target cards appeared and the experimenter verified the child's knowledge of the shapes and colors used in the task.

The experimenter then trained the child to sort cards by the dimension that would be used in the post-switch phase of the task. The child was told that they would play a color (shape) game. The experimenter explained the rules of the game and modeled sorting of the two training cards. The child was then asked to sort the two training cards him or herself. The training for the post-switch dimension was followed by the training for the pre-switch dimension. The experimenter gave supportive feedback during the training phase. Each child was given four different training cards (one per value per dimension), which could be presented a maximum of two times each. Children had to correctly sort all different training cards in order to pass the training phase.

The pre-switch phase began immediately after the training phase. Two different test cards were presented in a 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 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 questions, a test card was presented. The experimenter labeled the test card with the relevant dimension only (e.g., "This is a red one."). Children were given feedback on their responses to the knowledge questions but not on their sorting. A child had to sort six test cards correctly in order to pass the pre-switch phase. Children were given up to eight trials to reach this criterion.

At the start of the post-switch phase, the rules of the new game were explained and the testing started. Six trials were administered in the exact same way as the pre-switch trials.

Statistical approach

The statistical approach taken was to fit latent Markov models (Rabiner, 1989; Van de Pol & Langeheine, 1990) to the trial-by-trial accuracy data of the post-switch phase of the DCCS task using the package DepmixS4 (Visser & Speekenbrink, 2010) for the R statistical programming environment (R Development Core Team, 2009). This approach allowed for the identification of the number of latent states underlying the sequences of responses in the post-switch phase of the task. Moreover, with these models we could also quantify possible shifts between latent states over the course of the post-switch 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 shift 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 shift probability is the probability of moving to another latent state, conditional on being in a certain latent state.

The use of categorical latent variable techniques, such as latent Markov models, for classifying subjects into subgroups, instead of classifying participants by eye-balling (e.g. by using sum-scores of post-switch trials and an arbitrary cutoff) has a number of important advantages. First, with these techniques the criterion for classifying children into subgroups, such as perseverators and switchers, is based on sound statistical inference. The optimal choices for cutoff criteria require statistical modeling, otherwise classifying has a great danger to result in false positives. This means that one would wrongfully conclude that a specific strategy is used by some of the children. Second, the use of latent variable techniques provides the possibility of detecting hitherto unknown groups of participants that show similar behavior. In particular, the parameters of latent Markov models provide an estimate of the consistency of strategy use in children. If the probability correct of a subgroup would not deviate from .5, for example, their scores would not deviate from guessing. Third, the application of latent Markov models also allows for detecting regularities in sequential behavior, which is essential in differentiating dynamics of change. See Van der Maas & Straatemeijer (2008) for discussion on the necessity of applying categorical latent variable techniques in classifying strategy use. In the subsection *Classification into subgroups* of the *Results* section, we will illustrate the importance of these techniques by means of a small simulation study. We will first discuss the different statistical models that we will fit to the data.

In the case of continuous development with a rapid increase of the probability of a correct response, post-switch DCCS task data is consistent with a model with one state. The response probability of this state was modeled as a logistic function of age, which was accomplished by letting age act as a covariate on the response probability. Age was scaled, so that the age of the youngest children (36 months-old) was equal to zero. Two parameters were estimated in this model: the intercept (the response probability of the youngest children) and the coefficient β of the covariate on the response probability. This model is referred to as the model for continuous development.

In the case of step-wise development, post-switch DCCS task data is consistent with a model with two latent states that differ on the probability of a correct response: a perseveration state (with a low probability of a correct response) and a switch state (with a high probability of a correct response). In contrast to the continuous developmental model, the initial probability of the switch state was modeled as a logistic function of age by letting age act as a covariate on the initial probability of this state. Shifts between the two latent states over the course of the post-switch trials were not possible in the step-wise model. Four parameters were estimated in this model: the response probability of the perseveration state, the response probability of the switch state, the intercept (the initial probability of the switch state for the youngest children) and the coefficient β of the covariate on the initial probability of the switch state. This model is referred to as the model for step-wise development.

In the case of discontinuous development, post-switch DCCS task data is consistent with a model with a perseveration state (low probability of a correct response) and a switch state (high probability of a correct response)[1]. As in the model for step-wise development, the probability of being in the switch state at the first trial was a logistic function of age. However, in contrast with the model for step-wise development, reciprocal shifts between the two latent states over the course of the post-switch trials were possible. Hence, six parameters were estimated in the discontinuous model: the response probability of the perseveration state, the response probability of the switch state, the intercept (the initial probability of the switch state for the youngest children), the coefficient β of the covariate on the initial probability of the switch state, the shift probability from the perseveration state to the switch state and the shift probability from the switch state to the perseveration state. This model is referred to as the model for discontinuous development. In order to test if shifts in both directions contributed to a significantly better fit in the model for discontinuous development, a latent Markov model for discontinuous development with a one-way shift from the perseveration state to the switch state only was also estimated.

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 best. Hypotheses concerning the number of latent states in the latent Markov models were tested by two commonly used information criteria, AIC (Akaike, 1974) and BIC (Schwarz, 1978). Lower AIC's or BIC's indicated a better fitting model. Hypotheses concerning particular values of parameters, specifically whether the transition probabilities from the switch state to the perseveration state and vice versa equal zero or not, 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 (with shifts) was preferred. Otherwise the more parsimonious model (without shifts) was preferred.

2.3
Results

Standard analyses

Only the data of children that passed the training phase and the pre-switch phase were included in the analyses, which eliminated six children. No significant effects were found for gender, order of the presentation of the two versions, order of the sets of shapes and colors or order of the two sorting dimensions. Therefore, all results are collapsed across those variables. In the post-switch phase of the task, most of the children either responded correctly on zero or one (24%); or on five or six (62%) of the six post-switch trials. The frequency distribution of the number of correct post-switch trials in the three age groups is shown in Figure 2.1. 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 post-switch trials correctly were considered to have passed the post-switch phase. Consistent with reports in previous studies (e.g. Diamond, Carlson & Beck, 2005; Kloo & Perner, 2005; Towse, Redbond, Houston-Price & Cook, 2000; Zelazo, Müller, Frye & Marcovitch, 2003), most 3-year-olds performed poorly. Only 42% successfully switched dimensions during the post-switch phase. All 5-year-olds and 63% of the 4-year-olds successfully switched dimensions. There was a significant improvement over age in regards to whether children passed the post-switch phase, $\chi^2(df = 2, N = 93) = 21.59$, $p < .01$. Planned comparisons revealed that significantly more 5-year-olds than 4-year-olds passed the post-switch phase, $\chi^2(df = 1, n = 50) = 10.65$, $p < .01$. There was a trend towards a significant difference between 3-year-olds' and 4-year-olds' performance, with 4-year-olds performing slightly better, $\chi^2(df = 1, n = 70) = 2.95$, $p = .09$.

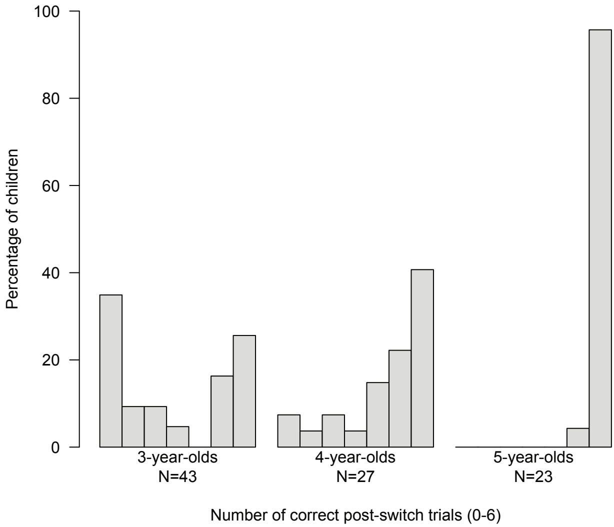

Figure 2.1 *Frequency distribution of the number of correct post-switch trials in the three age groups.*

Model-based analyses

The four different latent Markov models for continuous development, step-wise development, discontinuous development with reciprocal shifts, and discontinuous development with a one-way shift from perseverating to switching were fit to trial-by-trial data of the post-switch phase of the DCCS task. Table 2.1 shows the fit indices of the different models. Based on the information criteria AIC and BIC, the latent Markov models with two latent states fit the data better than the model with one latent state. The fit of the models for step-wise development and discontinuous development with a one-way shift was compared to the fit of the model for discontinuous development with reciprocal shifts by means of log-likelihood difference tests. Both tests were significant, step-wise: $\chi^2(df = 2, N = 93) = 76.00$, $p < .01$; discontinuous one-way shift: $\chi^2(df = 1, N = 93) = 11.05$, $p < .01$, therefore the model for discontinuous development with shifts back and forth between switching and perseverating was preferred. A graphical representation of the optimal latent

Markov model is shown in Figure 2.2. Consistent with a perseveration state and a switch state the response probability of one latent state was much lower (.01) than the response probability of the other latent state (.98). The probability to shift from the perseveration state to the switch state (.15) was higher than the probability to shift from the switch state to the perseveration state (.01). The initial probability of the switch state for 36-month-old children was .11. The initial probability of the switch state increased with age to an initial probability of the switch state of .97 for 71-month-old children, according to the function: 1 / (1 + exp (2.10 - 0.16 * age)) (age = age in months minus 36 months).

Table 2.1 *Fit indices of the latent Markov models for continuous development, step-wise development, discontinuous development with a one-way shift from perseverating to switching and discontinuous development with shifts both ways.*

Model	Log (L)	*df*	AIC	BIC	Δ log (L)	Δ *df*	*p* (Δ log (L))
Continuous	-266.07	2	536.15	544.79			
Step-wise	-199.18	4	406.36	423.66	76.00	2	.00
Discontinuous one-way shift	-166.71	5	343.41	365.03	11.05	1	.00
Discontinuous shifts both ways	-161.18	6	334.36	360.31			

Note. log (L) = Log-likelihood, df = degrees of freedom, AIC & 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. The model for continuous development was compared to the model for step-wise development and the models for discontinuous development by means of the information criteria AIC and BIC. The model for step-wise development and the model for discontinuous development with a one-way shift from perseverating to switching were compared to the model for discontinuous development with shifts both ways by means of log-likelihood difference tests.

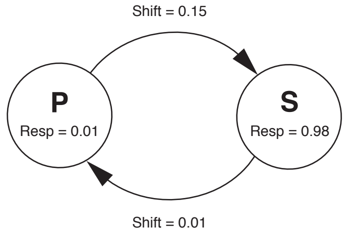

Figure 2.2 *Graphical representation of the latent Markov model for discontinuous development. P = perseveration state, S = switch state, Resp = response probability, Shift = shift probability. Note. The initial probability of the switch state (i.e. probability of the switch state at trial 1) was a logistic function of age; 1 / (1 + exp (2.10 - 0.16 * age)), age = age in months minus 36 months.*

Classification into subgroups

The model for discontinuous development described above provides a characterization of the entire group of children that were tested. To study developmental trends, we need to determine for individual children whether they were perseverators, switchers or whether they were in transition. For any given response pattern, we can compute the probability that that pattern was generated from only one state (either the switch state or the perseveration state) or from shifting between states. Such probabilities are called posterior probabilities. For example, a perseverator may have a response pattern of two trials incorrect, one trial correct, and three trials incorrect. According to the model, this pattern of responding has a high probability of being generated exclusively from the perseveration state. A child in transition may have a response pattern of three incorrect trials followed by three correct trials. Such a pattern most likely results from being in the perseverator state on the first three trials, and in the switch state thereafter. All children were assigned to the group that corresponded with their highest posterior probability.

To illustrate the importance of applying categorical latent variable models for classifying subjects into subgroups, we simulated DCCS post-switch data for the situation that there is no group of transitional children. The frequency distribution of the simulated data resembles the frequency distribution of the empirical data. We simulated a subgroup (31%) with a constant error rate of .8 and a subgroup (69%) with a constant error rate of .1 with 93 subjects and we added the ages of the empirical sample, such that the youngest subjects have an error rate of .8. If we now apply plausible, but arbitrary classification rules based on eyeballing: 22 (24%) children perseverate (< 2 correct trials); 58 (62%) children switch (5 or 6 correct trials); 13 (14%) children are in transition (2, 3, or 4 correct trials). Applying these rules results in false positives concerning the detection of transitional behavior. If one would require that transitional behavior shows some consistency of responding over time (e.g., at least 3 errors followed by at least 2 correct trials or a reversed sequence), it is concluded that 14% of the children shows random rather than transitional behavior. Because we simulated the data we know that also this classification is incorrect. Alternatively, we applied exact the same latent Markov analysis as we presented with the empirical data. For the simulated data the step-wise model was the optimal model (BIC = 513.56, compared to the continuous model, BIC = 527.71 and the discontinuous models, one-way shift BIC = 519.88, shifts both ways BIC = 526.19). The resulting optimal classification into subgroups is: a group of switchers (68%, > 3 correct trials, estimated P(error) = .1) and a group of perseverators (32%, < 4 correct trials, estimated P(error) = .86). Thus, the presence or absence of random behavior and transitional behavior can be detected by the application of latent Markov analysis. Moreover, an optimal cutoff resulted from the analysis (switchers have 4, 5, or 6 trials correct; perseverators have 1, 2, or 3 trials correct), which in this case deviates from standard procedures in DCCS data analysis (i.e., switching requires 5 or 6 correct post-switch trials; Zelazo, 2006).

Developmental trends

For the empirical data, the percentages of children categorized into the group of perseverators, children in transition, and switchers in the three age groups are shown in Figure 2.3. There was a significant age difference between the percentages of children categorized into the three groups, $\chi^2(df = 4, N = 93) = 31.44$, $p < .01$. A higher percentage of 3-year-olds was categorized as perseverators compared to the percentage of 4-year-olds and 5-year-olds categorized into that group. A higher percentage of 3-year-olds and 4-year-olds was categorized into the group of children in transition compared to 5-year-olds.

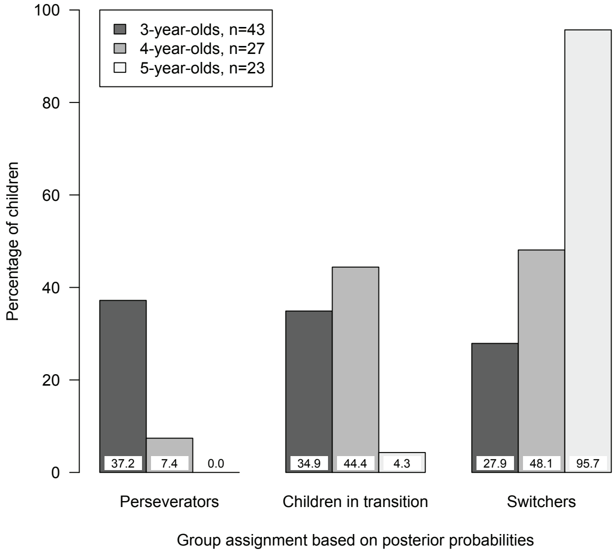

Figure 2.3 *Percentage of children categorized into the group of perseverators, children in transition, or switchers in the three age groups based on the posterior probabilities of the model for discontinuous development.*

To test for the presence of the catastrophe flag critical slowing down we calculated the reaction time (RT) difference score (mean RT of all post-switch trials minus mean RT of all pre-switch trials) of the children in transition, the children consistently perseverating, and the children consistently switching. The RT used was the time between when the experimenter presented the test card and when the child touched the target card or a sorting stack. The RTs of three children were not recorded correctly. Therefore, data of these children were left out of the analysis. The RT difference scores of three children deviated more than three standard deviations from the mean RT difference scores over all children. Below analyses were also done with these children's data excluded leading to identical results. On average children in transition did not have a significantly higher RT difference score (M = 850 ms, SE = 429) than children consistently perseverating (M = 341 ms, SE = 236) or switching (M = 168 ms, SE = 275), $F(2)$ = 1.167, p = .32, although differences are in the correct direction. Given that there was no speed instruction for the children, it is notable that the mean RT difference score of the children in transition marginally differed from zero, $t(26)$ = 1.98, p = .06. The mean RT difference score of the other two groups did not differ significantly from zero, perseverators: $t(17)$ = 1.45, p = .17; switchers: $t(44)$ = 0.61, p = .54.

2.4
Discussion

In this study we focused on exploring the dynamics of development on the DCCS task of children between ages 3 and 5. Fitting latent Markov models to the trial-by-trial data of the post-switch phase of the DCCS task showed that a model for discontinuous development, which is consistent with catastrophe theory (Thom, 1975), described the data best. That is, the model for discontinuous development fits the data better than the models of continuous and step-wise development. The model for discontinuous development consisted of two latent states: a perseveration state with a low probability of a correct response and a switch state with a high probability of a correct response. Most 3-year-olds perseverate on the first post-switch trial. Most 5-year-olds and half of the 4-year-olds switch correctly at the first post-switch trial. The finding that a large proportion of the 3- and 4-year-olds, but not the 5-year-olds, showed instabilities in performance and changes in performance over the course of the post-switch trials is new. Reciprocal shifts between perseverating and switching over the course of the post-switch trials were occurring. However, shifts from perseverating to switching were more probable than shifts from switching to perseverating. Based on these modeling results, we categorized children into three groups: perseverators, those in transition, and switchers. Three-year-olds were more likely to be categorized as perseverators compared to 4-year-olds and 5-year-olds. Three- and four-year-olds were more likely to be categorized as "in transition" compared to 5-year-olds. In agreement with catastrophe theory, we expected the transition group to show evidence of critical slowing down. That is, to show relatively high RTs for the post-switch trials. However, the mean RT difference score between the post-switch and the pre-switch phase did not differ significantly between the three groups. In the task instruction, no explicit reference was made to responding fast. Moreover, responses were made on a touch screen. Consequently, instruction and response format may have contributed to the high variance in RTs. Hence it is remarkable that only for the transitional group and not for the other two groups the difference between pre-switch RTs and post-switch RTs deviates from zero. The partial evidence for critical slowing down is an additional indication for discontinuous developmental change on the DCCS task.

Implications for computational models

Computational models of behavior and development on the DCCS task presented in the literature do make predictions about the dynamics of development on this task. However these predictions are not explicitly described or tested. In the next section we will discuss the consequences of our modeling results for these computational models. The two most important characteristics of the latent Markov model for discontinuous development are two modes of behavior characterized by a high and a low probability of a correct response, and the possible occurrence of reciprocal shifts between these two modes over the course of the post-switch trials. One way of implementing these dynamics in a computational system is by a model consisting of at least two sub systems that have a competitive interaction. The separate behavioral modes result from the fact that always one of the subsystems wins the competition. The outcome of the competition should change with development. In addition, during one phase of development, a transitional phase, the stability of the behavioral modes is limited such that shifts between modes can easily occur. We discuss whether relevant computational models incorporate the two important characteristics: two competitive behavioral modes and shifts between modes.

Marcovitch and Zelazo (2000) presented a cascade-correlation learning algorithm (CASCOR; Fahlman & Lebiere, 1990) of behavior and development on the DCCS task as an implementation of the cognitive complexity and control theory (Zelazo & Frye, 1997). CASCOR is a feed-forward neural network (with a generative algorithm), which does not consist of multiple competitive subsystems. Because of the absence of recurrent connections after learning, the model does not have equilibrium dynamics for its activity. Consequently, equivalent trials necessarily result in equivalent behavior. Hence, this network will not make shifts from one state to the other over the course of the post-switch trials. As in the latent Markov model for discontinuous development, Marcovitch and Zelazo found a group of children that passed the post-switch phase and a group of children that failed the post-switch phase. Additionally, their results showed a group of child networks with an intermediate performance level of 50% correct, which is not consistent with the current empirical results.

In contrast to the model of Marcovitch and Zelazo (2000), models of Buss and Spencer (2008) and Morton and Munakata (2002) are constructed from competitive subsystems or sub-processes. Buss and Spencer (2008) presented a dynamic neural field model based on a neural grounded view of the processes that underlie representations of colors, shapes and sorting space in the DCCS task (Johnson, Spencer & Schöner, 2008). The model consists of a layer of self-excitatory working memory neurons, a layer of inhibitory inter-neurons, and a long-term memory layer that is reciprocally coupled to the working memory layer. During the post-switch trials, there is competition between the long-term memory traces of the pre-switch trials and the formation of activity peaks in the working memory fields for the post-switch stimuli. Perseveration occurs when the long-term memory traces win this competition. The simulation of age related changes in the model favors activation of the location in the working memory field that is a match between sorting rule and presented stimulus. Because activity in the working memory field is following equilibrium dynamics, it is expected that with gradual variation of this variable no intermediate performance level would emerge. This finding is consistent with the two latent states of the latent Markov model for discontinuous development. However, shifts between the two states are not possible in their model. Stability of initial behavioral mode after the switch is always increased during the post-switch trials. Hence, in the current version of the model, it is impossible to shift between behavioral modes during post-switch trials.

Morton and Munakata (2002) also presented a neural network model that is based on multiple competitive systems, that is, latent and active memory traces (Munakata, 1998). Latent representations take the form of strengthened connections between units, and active representations take the form of sustained activity in processing units. An internal representations layer interacts with a prefrontal cortex (PFC) layer at an output layer such that incongruent activity results in a conflict. Equilibrium dynamics of activity is found in the PFC and the output layer, resulting in different behavioral modes in the output layer. During the post-switch phase, the latent representation of the pre-switch rules competes with the active representation of the post-switch rules. Morton and Munakata simulated age-related changes in their model by increasing the strength of the recurrent excitatory connections of the PFC units to themselves, which favors the behavioral mode congruent with the post-switch rules. Consistent with the latent Markov model for discontinuous development, results of the model of Morton and Munakata showed that the youngest networks fail the post-switch phase and the oldest networks pass the post-switch phase. In contrast to our results, their computational results also included a group of children with an intermediate performance level scoring a 50 percent correct response on all post-switch trials. Reciprocal shifts between perseverating and switching over the course of the post-switch trials are not very likely in their model for a comparable reason as in the model of Buss and Spencer (2008): the behavioral mode that is active during a trial is strengthened during that trial. Consequently, it is very unlikely that after a first correct trial an incorrect response will be made in the subsequent trials, and vice versa.

The three computational models of behavior and development on the DCCS task presented in literature can all incorporate two separate states: a perseveration state and a switch state. However, none of the three computational models incorporate shifts between these states over the course of the post-switch trials. Adding noise to the internal system might be a possible solution to incorporate these results into the conflict models of Buss and Spencer (2008) and Morton and Munakata (2002). Note, however, that due to the nonlinear dynamics of these models, adding noise could affect the equilibrium dynamics of the model importantly (e.g., Katada & Nishimura, 2009).

The competing memory systems theory proposes that limited cognitive flexibility for different task domains is partly caused by limitations of the brain systems that are critical for working memory (Brace, Morton & Munakata, 2006; Stedron, Sahni & Munakata, 2005; Morton & Munakata, 2002; Munakata, 1998; Cohen & Servan-Schreiber, 1992; Cohen, Dunbar & McClelland, 1990). Stedron et al., for example, show that this hypothesis cannot only account for task with hidden targets, but also for tasks without apparent memory demands. The main role of the working memory in both cases would be to direct attention to relevant stimuli. They show that the neural network implementation of the competing memory systems theory cannot only account for DCCS results but also for performance on other tasks, such as the cloth-pulling task. An interesting test for this unifying hypothesis would be that the developmental dynamics for all tasks is comparable. That is, for example, that there exist a small group of transitional children with instable performance also for other task domains. Below, we will present a general model for the dynamics of development that could apply for the DCCS task, but which could also be interpreted in other task domains.

Future Directions

In the current project we studied the dynamics of development on the DCCS task by fitting latent Markov models on the trial-by-trial data of the post-switch phase of this task. Testing specific developmental hypotheses about the variables that control development would be possible by making a substantive interpretation of a catastrophe model. Subsequently, additional catastrophe flags could be tested in the behavior of children on the DCCS task.

To make a substantive interpretation of a catastrophe model, we propose a model that is consistent with the current empirical results and that can be used as a starting point for future research: a conflict cusp model (Zeeman, 1976; Van der Maas & Molenaar, 1992) of the transition from perseverating to switching on the post-switch phase of the DCCS task. In the cusp model, which is displayed in Figure 2.4, the change in the dependent variable depends on continuous variation in two independent variables. The dependent variable in our cusp model of DCCS development is the probability of a correct response on a post-switch trial, and it is represented by the z-axis in Figure 2.4. The a-axis represents the strength of the activation of the pre-switch rules, and the b-axis represents the strength of the activation of the post-switch rules. Consequently, as can be read of from figure 2.4, high activation of the pre-switch rules (high values on the a-axis) combined with low activation of the post-switch rules (low value on b-axis) leads to a low probability of correct post-switch performance, hence perseverative behavior. In contrast, low activation of the pre-switch rules (low value on the a-axis), combined with high activation of the post-switch rules (high value on the b-axis) leads to a high probability of correct post-switch performance. According to this model, when during the post-shift phase of the DCCS task, the strength of the activation of the pre-switch rules is roughly equal to the strength of the activation of the post-switch rules, the rules are in competition with one another and the child is in transition. This means that both correct and incorrect performance is part of the behavioral repertoire, and the child can oscillate between these behaviors (Van der Maas & Molenaar, 1992). Which rules such a child actually applies depends on the history of performance (did the child apply the pre-switch rules on former trials), a bias for a particular stimulus dimension or value, and perturbations of his or her behavior. A perturbation can be anything that influences the strength of the activation of the pre-switch rules or the post-switch rules. Examples of perturbations that can cause a shift from perseverating to switching are the repetition of the post-switch sorting rules, feedback on the knowledge questions the experimenter asks the child and labeling of the test card with the relevant dimension only. Perturbations that can cause a shift from switching to perseverating are distractions from the task, such as noises in the test environment. Also other indications of instabilities that are reported in literature, such as dissociations between knowledge and action (Morton & Munakata, 2002), could be interpreted as *anomalous variance*, which is one of the catastrophe flags (Van der Maas & Molenaar, 1992).

With the conflict cusp model that we presented so far, we do not make specific, substantial claims about the mechanism for DCCS task performance and development, such as neural networks do. Nevertheless, the cusp model importantly constrains the set of possible neural network models that do describe a more specific mechanism. Moreover, the general interpretation of the cusp model for DCCS development is consistent with multiple theoretical frameworks. A more specific interpretation of the cusp model according to the competing memory systems account for perseveration (Munakata, 1998), for example, would suggest the following control variables in the conflict model: a) the strength of the latent memory traces of the pre-switch rules; b) the strength of the active memory traces of the post-switch rules. With such a more specific interpretation of the model, we make very specific claims about DCCS performance and development.

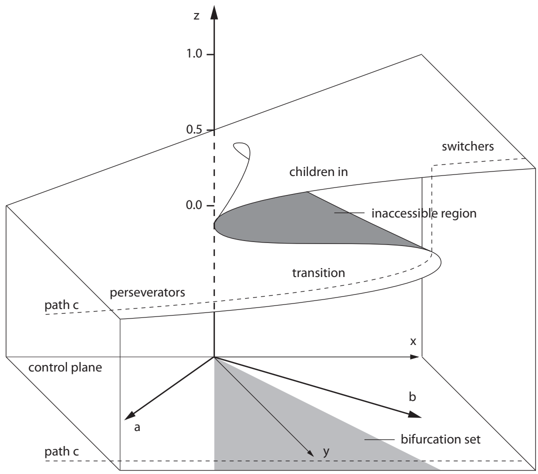

Figure 2.4 *Conflict cusp model for the transition from perseverating to switching on the post-switch phase of the DCCS task. z = dependent variable; probability of a correct response on a post-switch trial, a = independent variable 1; strength of the activation of the pre-switch rules, b = independent variable 2; strength of the activation of the post-switch rules, x = normal variable; difference in strength of the activation of the post-switch rules and the activation of the pre-switch rules (a-b), y = splitting variable; total strength of the activation of the post-switch rules and the activation of the pre-switch rules (a+b).*

Specific predictions can be derived from catastrophe flags. Examples of catastrophe flags that can be studied in future research are *sudden jumps, hysteresis* and *divergence*. Sudden jumps from perseverating to switching or from switching to perseverating are the result of changes in the normal variable. The normal variable is represented on the x-axis in Figure 2.4 and can be interpreted as the difference between the strength of the activation of the post-switch rules and the strength of the activation of the pre-switch rules, a measure of conflict. Increasing the normal variable results in a sudden jump from perseverating to switching and decreasing the normal variable results in a sudden jump from switching to perseverating. The phenomenon that the jump from perseverating to switching takes place at a higher value of the normal variable than the jump from switching to perseverating, is called hysteresis. The presence of sudden jumps and hysteresis can be studied by continuously manipulating the normal variable in both directions. A possible way of continuously manipulating the level of conflict between the pre-switch rules and the post-switch rules might be adding flankers to the cards that need to be sorted. Jordan and Morton (2008) showed that adding flankers that were congruent with the post-switch rules significantly facilitated 3-year-olds use of the correct rules in the post-switch phase of the DCCS task. By continuously varying the distance of the flankers to the test cards the size of this effect changed (Jordan & Morton, 2007). A higher proportion of children passed the task when flankers were close to the test cards than when the flankers were further away. By varying the distance of the flankers to the test cards from not present to very close over many trials, a child in transition that first perseverates might make a sudden jump to switching. In contrast, by varying the distance of the flankers from very close to not present, might make a child in transition that first successfully switched make a sudden jump to perseverating. We would expect that the mean distance of the flankers to the test cards of children that make a jump upward is smaller than the mean distance of the flankers to the test cards of children that make a jump downward. Such a hysteresis experiment would test the hypothesis that the level of conflict between the pre-switch rules and the post-switch rules controls development.

The variable represented on the y-axis in Figure 2.4 is called the splitting variable. This variable is the total strength of the activation of the pre-switch and the post-switch rules. When the splitting variable is increased, the jump between perseverating and switching becomes more extreme. This is called divergence. Labeling test cards or repeating sorting rules or knowledge questions on every pre-switch or post-switch trial manipulates the strength of both the activation of the pre-switch rules and the activation of the post-switch rules. With the absence of this manipulation, we would expect that children make more errors during performance, resulting in a less pronounced bimodal distribution of the sum-scores of the post-switch trials. These future studies would further our understanding of the dynamics of development on the DCCS task and test specific developmental hypotheses about the variables controlling the developmental process.

Conclusion

The dynamics of development on the DCCS task is best described by a model of discontinuous development. However, supplementary empirical research is needed to get a more complete picture of the developmental dynamics and test specific developmental hypotheses about the variables controlling the developmental process. In addition to a perseveration group and a switch group, a group of children in transition that showed shifts between perseverating and switching during the post-switch trials, could be distinguished. Computational models of behavior and development on the DCCS task presented in literature cannot, in their current forms, explain our results. However, adding noise to the internal system might be a (partial) solution to incorporate our results in the conflict models of Buss and Spencer (2008) and Morton and Munakata (2002). The proposed conflict cusp model for the transition from perseverating to switching on the post-switch phase of the DCCS task could serve as a starting point for future studies about the dynamics of DCCS performance development.

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Footnote

[1] We also considered the stayer-switcher mixed latent Markov model proposed by Van de Pol & Langeheine (1990) and Schmittmann, Dolan, Van der Maas &

McNeal (2005). Theoretically, this model would be better for describing three groups: perseverators, switchers, and transitional children. However, a small simulation study showed that fitting such a model to data comparable to our study (i.e., simulated data with the expected three groups) would not result in a stable solution.