Mata, Rui ; von Helversen, Bettina ; Rieskamp, Jörg

When easy comes hard: The development of adaptive strategy selection

Journal Article as: peer-reviewed accepted version (Postprint)

DOI of this document*(secondary publication): https://doi.org/10.26092/elib/3449

Publication date of this document: 08/11/2024

* for better findability or for reliable citation

Recommended Citation (primary publication/Version of Record) incl. DOI:

Mata, R., von Helversen, B. and Rieskamp, J. (2011), When Easy Comes Hard: The Development of Adaptive Strategy Selection. Child Development, 82: 687-700. https://doi.org/10.1111/j.1467-8624.2010.01535.x

When Easy Comes Hard: The Development of Adaptive Strategy Selection

Rui Mata
Max Planck Institute for Human Development, Berlin and University of Lisbon

Bettina von Helversen and Jörg Rieskamp
Max Planck Institute for Human Development, Berlin and University of Basel

Can children learn to select the right strategy for a given problem? In one experiment, 9- to 10-year-olds (N = 50), 11- to 12-year-olds (N = 50), and adults (N = 50) made probabilistic inferences. Participants encountered environments favoring either an information-intensive strategy that integrates all available information or an information-frugal strategy that relies only on the most valid pieces of information. Nine- to 10-year-olds but not older children or adults had more difficulties learning to select an information-frugal strategy than an information-intensive strategy. This counterintuitive finding is explained by children's less developed ability to selectively attend to relevant information, an ability that seems to develop during late childhood. The results suggest that whether a strategy can be considered ''easy'' depends on the development of specific cognitive abilities.

The ability to consider the right amount of information is crucial to making good choices. In some cases, it may be appropriate to focus on single pieces of information, while other times one may have to use more information-intensive strategies that integrate several pieces of information to make the correct decision. But which decision strategies are available to children and what factors determine children's ability to learn about which one is most appropriate in a given situation?

In this article, we claim that frugal decision strategies that rely on single cues and more information-intensive ones that consider additional information tend to exploit distinct abilities. Specifically, information-frugal decision strategies often require ignoring available information and, consequently, demand selective attention to specific cues. In contrast, information-intensive compensatory strategies have more pronounced memory requirements and mostly tap the ability to integrate information. These underlying abilities, selective attention and information integration, however, may develop at different rates across ontogenetic time, leading to developmental trends in preferences for strategies and constraints in strategy selection. Crucially, these differences can lead to counterintuitive predictions, namely, that children prefer information-intensive strategies and have a hard time learning to select frugal strategies usually viewed as computationally simpler. In other words, for children, easy may come hard.

Our thanks go to Cornelia Büchling, Gregor Caregnato, Uwe Czienskowski, Stefanie Dabrowski, Robert Habicht, Jutta Mata, and Sven Ohl. This work was supported by a postdoctoral fellowship of the Portuguese Science and Technology Foundation to the first author, and a research grant from the German research foundation to the second and third authors (RI 1226/5).

Correspondence concerning this article should be addressed to Rui Mata, Faculdade de Psicologia, Universidade de Lisboa, Alameda da Universidade, 1649-013 Lisboa, Portugal. Electronic mail may be sent to ruimata@ruimata.com.

The Development of Multiple-Cue Inference

Multiple-cue inference, the ability to derive conclusions from several premises or cues, develops considerably across childhood and adolescence (Zimmerman, 2007). Research on the development of estimation, categorization, and reasoning, suggests that, on the one hand, young children have difficulties focusing on individual pieces of information and that there is a developmental trend toward being able to selectively focus on relevant cues. For example, Miklich and Gillis (1975) compared the learning abilities of 8- and 14-year-olds in an estimation task requiring the integration of three cues to estimate a criterion. In one condition, all three cues had the same validity and learning performance was similar across age groups. However, in a condition in which only one cue was valid, the younger participants had more difficulties than older ones. Likewise, some findings suggest that young children tend to perform induction relying on multiple sources of information, whereas preadolescents are able to rely on a single source (Hayes, McKinnon, & Sweller, 2008; Sloutsky, Lo, & Fischer, 2001). Also, reasoning research suggests that younger children and preadolescents are more likely than adolescents or adults to consider uninformative factors or experiments when reasoning about scientific experiments (Klahr, Fay, & Dunbar, 1993; Schauble, 1996). On the other hand, there is a developmental trend in the ability of children and adolescents to integrate multiple cues. For example, the ability to consider several cues to estimate a continuous criterion has been shown to increase in late childhood and adolescence (Lafon, Chasseigne, & Mullet, 2004; Montanelli, 1972). Work on categorization suggests an age trend in the ability to integrate multiple cues when categorizing objects (von Helversen, Mata, & Olsson, 2010). Finally, children and young adolescents show difficulties relative to adults in integrating multiple cues when reasoning about scientific problems (Kuhn, Iordanou, Pease, & Wirkala, 2008). In sum, there are two developmental trends in multiple-cue inference. First, there is an increased tendency to be able to selectively focus on relevant information. Second, there is a trend toward effective information integration. Our goal is to evaluate the potential impact of such trends on children's decision making.

Learning to Choose: The Development of Compensatory and Noncompensatory Decision Making

Decision abilities develop considerably throughout the life span (Klaczynski, 2001; Reyna & Farley, 2006). For example, young children have difficulties in learning from feedback about the value of *decision options* due to both cognitive and motivational factors, but this ability develops significantly across childhood and adolescence (Crone & Van der Molen, 2007; Hooper, Luciana, Conklin, & Yarger, 2004). In this article, we address how children are able to learn the value of *decision strategies*.

Decision strategies specify how a person gathers and integrates information to make a decision. When deciding which food is most healthy, a child has available many different pieces of information (i.e., cues), such as the food's category (animal vs. vegetable), taste, smell, and so on (Scheibehenne, Miesler, & Todd, 2007). Likewise, when crossing the street, a child can use several cues, such as the speed and the distance of approaching traffic, to make a decision about whether it is safe to cross (Hoffrage, Weber, Hertwig, & Chase, 2003).

What decision strategies can people apply in these or other similar situations? Decision makers may select information-intensive compensatory strategies, for example, a weighted-additive rule (WADD; e.g., Payne, Bettman, & Johnson, 1993). WADD integrates all available information by adding cue values weighted by their importance. Alternatively, a person may rely on a less cognitively demanding strategy that assigns equal weights to cues and adds them using a Tally strategy (Gigerenzer & Goldstein, 1996). In contrast, when using an information-frugal noncompensatory strategy, such as take the best (TTB; Gigerenzer & Goldstein, 1996), one focuses on the single most important cue to make a decision and ignores any further information. Whether a strategy will lead to correct inferences depends on the statistical structure of the environment, such as the association between the cues and the criterion, and the correlation between cues. For example, Dieckmann and Rieskamp (2007) have shown that in environments where cues are positively correlated with each other, a noncompensatory strategy is sufficient to make good inferences with little information and is thus both accurate and economical. In contrast, in environments where cues are slightly or negatively intercorrelated, a compensatory strategy is best, as it allows for trade-offs.

What decision strategies are available to children? Children are likely to have a number of strategies available to them, but there may be systematic patterns in the development of adaptive strategy selection, that is, the ability to select the right strategy as a function of the situation (Lemaire & Siegler, 1995; Siegler, 1999). Some research suggests that young children may be limited to using information-frugal, noncompensatory decision strategies due to working memory limitations—we refer to this idea as the *memory hypothesis*. In general, information-intensive compensatory strategies require more computations and they are often considered as more effortful to apply than noncompensatory strategies (e.g., Payne et al., 1993). This view receives support from various sources: Young adults rely more frequently on simple noncompensatory strategies when many options have to be compared (e.g., Ford, Schmitt, Schechtman, Hults, & Doherty, 1989) or when under time pressure (Rieskamp & Hoffrage, 2008). Likewise, Bereby-Meyer, Assor, and Katz (2004) found that 8- to 9-year-olds seem to rely more often on noncompensatory strategies than 12- to

13-year-olds, and Mata, Schooler, and Rieskamp (2007) showed an increase in the reliance on noncompensatory decision strategies in older adults. Furthermore, Mata et al. showed that increased reliance on noncompensatory strategies was related to age-related decline in cognitive abilities, suggesting that compensatory strategies place higher requirements on cognitive capacities such as working memory. These results are important for the development of strategy selection in childhood because children show similar levels of performance in cognitive tasks to that of older adults (e.g., Case, 1985; Kail, 1991; Kail & Salthouse, 1994). In sum, children up to 9 years old may have difficulties in applying information-intensive, compensatory strategies and thus may rely more on information-frugal, noncompensatory strategies (Bereby-Meyer et al., 2004).

At the same time, however, children's reliance on decision strategies may be limited by their ability to selectively allocate their attention—an idea we refer to as the *attention allocation hypothesis*. The successful application of noncompensatory strategies requires focusing on relevant, valid information, and ignoring less valid sources. The ability to ignore information in predecisional information search seems to develop across childhood (Davidson, 1991a, 1991b, 1996; Gregan-Paxton & Roedder John, 1995, 1997; Howse, Best, & Stone, 2003). For example, Davidson (1991a) showed that 7- to 9-year-olds searched for more irrelevant information than 9- to 12-year-olds. Similarly, Gregan-Paxton and Roedder John (1997) have shown that 9-year-olds benefit from increased information costs to prevent them from searching irrelevant information before making a decision.

In sum, there are different strategies available to decision makers that differ in their memory and selective attention requirements. While some research suggests that children may tend to select information-frugal noncompensatory strategies that have little working memory requirements, other findings suggest that children may prefer compensatory strategies that do not require selective attention to information. The goal of this article is to test these competing views. In the following, we report a study aimed at investigating children's preferences for different types of strategies and, more importantly, their ability to learn which type is most appropriate from performance feedback. Our approach thus helps understand children's ability to adaptively select and apply both compensatory and noncompensatory strategies.

The Current Study: Going to the Races

We examined 9- to 10-year-olds, 11- to 12-year-olds, and adults' ability to adapt their decision strategies to one of two task environments (noncompensatory vs. compensatory). We focused on the relatively narrow age range in children because maturation of prefrontal cortical areas associated with working memory and selective attention have been shown to develop considerably in the 9–12 age range (Bunge & Zelazo, 2006; Diamond, 2001). These findings also match previous work on the development of decision making suggesting significant change in strategy use in this age range (Davidson, 1996; Gregan-Paxton & Roedder John, 1997; Klayman, 1985).

Our participants' task was to make a series of inferences about which of three cars would win a race based on six dichotomous cues such as each car's horsepower, type of fuel, tires, and so on. Moreover, after an initial phase in which participants received no feedback concerning their choices, participants received feedback favoring either a compensatory strategy WADD (compensatory environment) or a noncompensatory strategy TTB (noncompensatory environment). We thus were able to go beyond assessing children's initial strategy preferences and evaluate their strategy selection given substantial learning opportunity.

Our experimental setting allowed us to contrast two perspectives on the development of adaptive strategy selection: First, the memory hypothesis states that children's cognitive limitations in information storage and manipulation will constrain the selection of information-intensive compensatory strategies even after considerable learning opportunity. In contrast, the attention allocation hypothesis suggests that children's attention allocation abilities pose a main constraint in strategy selection and that younger children should perform particularly poorly in an environment favoring the use of a noncompensatory strategy that requires selective attention to particular pieces of information.

Method

Participants

Fifty fourth-grade children (mean age = 9.3 years, *SD* = 0.5; 50% female), 50 sixth-grade children (mean age = 11.5, *SD* = 0.6; 52% female), and 50 young adults (mean age = 22.7, *SD* = 2.2; 56% female) participated in the study. Children were recruited from a Berlin school. Young adults were students at the Free University of Berlin.

Material

To determine which cue labels to use for our car race task and to ensure that the task matched participants' prior beliefs we asked independent samples of 9- to 10-year-olds ($N = 26$), 11- to 12-year-olds ($N = 51$), and young adults ($N = 31$) to rate the importance of 14 potential cues in determining how fast a car is on a scale from 1 (*not important*) to 7 (*extremely important*). We then selected seven cue labels minimizing both age and gender differences in the subjective importance of each cue and constructed two sets of six cue labels, which differed in the dispersion of the six cues' importance. Note that the two sets were identical with the exception that a cue with an extremely positive rating (horsepower) was substituted by a cue with a moderate rating (cooling system). The set of labels with more dispersed importance ratings was used to label cues in the noncompensatory environment (horsepower, number of cylinders, tires, fuel, spoiler, suspension; with the respective mean importance ratings of 6.2, 5.3, 4.7, 4.3, 3.6, 2.8) and the less dispersed set was used to label cues in the compensatory environment (number of cylinders, tires, fuel, spoiler, cooling system, suspension; with the respective mean importance ratings of 5.3, 4.7, 4.3, 3.7, 3.6, 2.8). All cues were given dichotomous values; for example, a car could have normal or special tires, and use normal or special fuel. The experimental software used was a modification of that developed by Czienskowski (2004).

Design

The experimental design had three factors: environment (between subjects), trial block (within subjects), and age group. Altogether, participants made 210 decisions, corresponding to seven repetitions (blocks) of an item set of 30 items presented in random order within each block. Feedback was provided after the first block to enable learning. In each of the seven blocks of the noncompensatory environment, TTB reached an accuracy level of 90% (i.e., 27 correct predictions of 30) while both WADD and Tally reached an accuracy level of 60% (i.e., 18 correct predictions of 30). In the compensatory environment, the strategies' accuracies were reversed with an accuracy of 60% for TTB, 75% for Tally, and 90% for WADD. Overall, the three strategies made different predictions for about one third of the items. To avoid limiting our conclusions by using only one specific item set, we followed the constraints mentioned above to create a different item set for each participant within an age group. Consequently, we constructed a total of 50 environments, each being assigned to one participant in each age group. The age groups were thus matched regarding the item sets (yoked design). Because each participant within an age group experienced a slightly different item set, the validity of each cue was slightly different for each participant. Cue validity can be understood as the predictive value of each cue and is calculated as the proportion of times the cue enables the right decision to be made, given that it discriminates between the options. The mean cue validities in the noncompensatory environment were .77, .66, .57, .50, .44, .36, and in the compensatory environment .71, .65, .59, .52, .45, .38. The cue validities were assigned to the cue labels (e.g., horsepower, number of cylinders) so as to reflect the subjective importance of each cue (see the Material section).

Procedure

Participants were first told they would be making a number of inferences about which of three race cars would win a particular race on the basis of six characteristics (i.e., cues) describing each car. Participants were told that they would make 210 inferences, how much they would earn for a correct inference (€0.10) and how much they would have to pay for an incorrect inference (€0.05). The concept of cue validity was explained to the participants in the instructions. More specifically, participants were informed that a cue with a validity of .70 would lead to a correct decision in 70 of 100 cases in which it discriminated, while a cue with a validity of .5 would lead to a correct decision in 50 of 100 cases. To ensure that children grasped the concept, the experimenter always asked which of two cues with differing validities would be better to make an inference. If a participant answered incorrectly, the experimenter explained why the other cue would have been better and gave a second example question. All participants correctly answered the second question. Participants were also told which of the two possible values of each cue indicated a higher likelihood of winning the race.

The computer display used to make decisions had two main parts (see Figure 1). The upper part

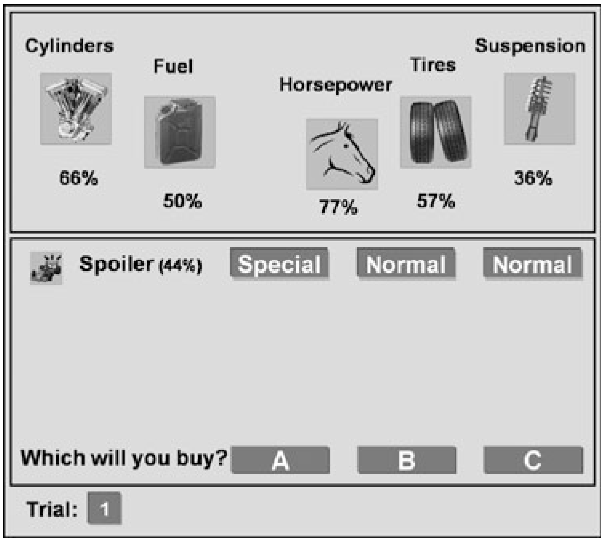

Figure 1. Information board used in the experiment.
Note. Participants could find out about the cars' characteristics by clicking on the icons at the top of the screen. The cue values for all three alternatives were then presented in the lower section of the display.

of the display presented cue icons for all six cues and the respective validities were shown below each cue icon. The positions at which the characteristics were displayed at the top of the screen were the same for all decisions for a given participant but varied randomly across participants. Participants were able to choose a car at any time during a trial by clicking on one of three buttons assigned to each option (A, B, C) on the lower half of the display. Participants were thus not forced to search for any information before making a decision; however, they had the possibility of making informed decisions by looking up the cars' cue values. To look up cue values, participants could click on the corresponding cue icon on the upper part of the display. When a cue icon was clicked upon, the three cue values corresponding to the attributes of the three race cars on that cue were revealed and remained visible until a decision was made. The order in which characteristics appeared on the lower part of the screen was determined by the order in which the cues had been clicked upon in the upper part of the display. In those trials in which feedback was provided, each decision was followed by either a green *correct* box with a ''smiley'' or a red *wrong* box with a ''frowny.''

After performing the decision task, participants completed a verbal knowledge test (Lehrl, 1999) and two measures of fluid abilities (Wechsler, 1981): the digit-symbol substitution task and the digit span task (forward and backward).

Results

We first provide an overview of participants' performance by reporting their payoffs. Second, we report participants' information search and strategy classification results. Finally, we use a computational model (Rieskamp & Otto, 2006) to describe participants' learning processes and provide an explanation for age differences in strategy selection.

Payoff

Visual inspection of the data showed that the younger children's payoffs increased over the course of the experiment but then decreased slightly in the last two to three blocks. In contrast, payoffs increased over time for the other age groups. This seems to have been due to the 9- to 10-year-olds becoming tired in the final blocks. To avoid drawing conclusions about age differences simply due to the younger children becoming tired over the course of the study, we conducted separate analyses for the first four blocks of the experiment as well as for the full set of seven blocks. Overall, the results of the first four blocks generalize to the full experiment, but as expected, age differences become slightly more pronounced when the final blocks are considered in the analyses.

We first conducted an analysis of variance (ANOVA) with the cumulative payoff at the end of the fourth block as the dependent variable and age group, environment, and their interaction as independent variables. The analysis revealed an effect of age group, $F(2, 144) = 11.88$, $p < .001$, $\eta_p^2 = .14$, and an Age Group × Environment interaction, $F(2, 144) = 3.8$, $p = .03$, $\eta_p^2 = .05$, but no main effect of environment, $F(2, 144) = 2.37$, $p = .13$, $\eta_p^2 = .02$. To better distinguish between age groups and understand the interaction effect, we additionally conducted separate ANOVAs comparing the three age groups in a pairwise fashion. The 9- to 10-year-olds reached significantly lower payoffs ($M = 6.2$, $SD = 1.9$) compared to those of the older children ($M = 7.4$, $SD = 1.7$), $F(1, 99) = 10.73$, $p = .001$, $\eta_p^2 = .10$, and the adults ($M = 7.8$, $SD = 1.3$), $F(1, 99) = 22.84$, $p < .001$, $\eta_p^2 = .19$. Additionally, comparing 9- to 10-year-olds to adults we found an effect of environment, $F(1, 99) = 4.49$, $p = .04$, $\eta_p^2 = .05$, qualified by an Age × Environment interaction,

Table 1
Payoffs and Means (Standard Deviations) of the Information Search Variables by Age Group

	Children 9–10				Children 11–12				Adults 20–25			
	NC		C		NC		C		NC		C	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Blocks 1–4												
Payoff	5.5	2.0	7.0	1.6	7.5	1.7	7.3	1.6	7.8	1.3	7.7	1.4
PROP	.81	.21	.93	.15	.87	.19	.93	.13	.79	.18	.84	.19
VALIDITY	.10	.22	.22	.38	.60	.42	.63	.43	.75	.36	.66	.41
DISPLAY	.44	.40	.45	.43	.23	.40	.17	.36	.04	.13	.18	.37
Blocks 1–7												
Payoff	9.9	3.8	11.9	2.5	13.8	2.9	13.0	2.9	14.7	2.1	13.9	2.3
PROP	.80	.21	.92	.14	.85	.19	.94	.12	.76	.19	.86	.17
VALIDITY	.14	.26	.23	.39	.63	.42	.63	.44	.79	.35	.70	.40
DISPLAY	.46	.41	.44	.44	.23	.41	.18	.37	.02	.07	.18	.36

Note. NC = noncompensatory environment; C = compensatory environment; PROP = average proportion of information searched per trial; VALIDITY = proportion of trials in which the validity of cues was followed; DISPLAY = proportion of trials in which information was searched in the order of the display.

$F(1, 99) = 5.87$, $p = .02$, $\eta_p^2 = .06$. As can be seen in Table 1, younger children reached a significantly lower payoff in the noncompensatory compared to the compensatory environment. Likewise, 9- to 10-year-olds seemed to reach lower payoffs relative to 11- to 12-year-olds, particularly in the noncompensatory environment as shown by a marginal effect of environment, $F(1, 99) = 3.55$, $p = .06$, $\eta_p^2 = .04$, qualified by an Age × Environment interaction $F(1, 99) = 4.96$, $p = .03$, $\eta_p^2 = .05$. In contrast, the adults' payoffs and that of the 11- to 12-year-olds did not differ significantly, $F(1, 99) = 1.47$, $p = .23$, $\eta_p^2 = .02$, and we found no effect of environment, $F(1, 99) = 0.13$, $p = .72$, $\eta_p^2 < .01$, nor an Age × Environment interaction, $F(1, 99) = 0.002$, $p = .97$, $\eta_p^2 < .01$.

An analysis of variance for all seven blocks with the total payoff as the dependent variable revealed similar results compared to the analysis of the first four blocks. We found an effect of age group, $F(2, 144) = 19.72$, $p < .001$, $\eta_p^2 = .22$, and an Age Group × Environment interaction, $F(2, 144) = 4.02$, $p = .02$, $\eta_p^2 = .05$, but no effect of environment, $F(2, 144) = 0.14$, $p = .71$, $\eta_p^2 = .001$. Consequently, the results for the first half of the experiment generalize to the full experiment. However, as expected from the younger children becoming tired over time, while the older children and adults continued to learn, the differences between the 9- to 10-year-olds and the older age groups became more pronounced in the second half. For example, age differences in payoff were larger when all blocks were considered ($\eta_p^2 = .22$) compared to when only the first four blocks were examined ($\eta_p^2 = .14$).

Our analysis of payoffs thus provides evidence for the attention allocation hypothesis. The results suggest that 9- to 10-year-olds had difficulties in selectively attending to information, an ability required to successfully apply noncompensatory strategies: While 11- to 12-year-olds resembled adults in their performance, the younger 9- to 10-year-olds showed poorer payoffs and fared particularly poorly in the noncompensatory compared to the compensatory environment.

Information Search

To describe participants' information search, we considered the average proportion of information searched per trial (PROP) and two variables describing the pattern of information search: the proportion of trials in which information was searched in the order of the cues' validities (VALIDITY) and the proportion of trials in which information was searched in the order of the display (DISPLAY). The results are summarized in Table 1.

We conducted separate ANOVAs with each search variable as the dependent variable and age group and environment as independent variables. Again, we focused initially on the results from the first four blocks. Concerning PROP, we found a small effect of age, $F(2, 144) = 2.99$, $p = .05$, $\eta_p^2 = .04$. As can be seen in Table 1, adults searched for slightly less information compared to children, which may be an indicator that they were more strategic in their information search. We also identified a main effect of environment, $F(2, 144) =$

8.28, $p = .005$, $\eta_p^2 = .05$, suggesting participants generally searched for more information in the compensatory environment: This was expected as the compensatory environment favored the use of a more information-greedy strategy compared to the noncompensatory environment. We found no Age × Environment interaction, $F(2, 144) = 0.72$, $p = .49$, $\eta_p^2 = .01$.

Concerning the pattern of search, adults and 11- to 12-year-olds were more likely to search for information in order of validity compared to 9- to 10-year-olds, suggesting younger children relied less on a noncompensatory strategy such as TTB that involves validity-ordered search for information. We identified significant age-related effects regarding VALIDITY, $F(2, 144) = 30.49$, $p < .001$, $\eta_p^2 = .3$, but no effect of environment, $F(2, 144) = .10$, $p = .76$, $\eta_p^2 = .001$, or Environment × Age group interaction, $F(2, 144) = .96$, $p = .39$, $\eta_p^2 = .01$. In turn, adults and 11- to 12-year-olds were less likely to search for information in order of display compared to 9- to 10-year-olds, suggesting younger children tended to use more of a spatial strategy when searching for information. We identified significant age-related effects regarding DISPLAY, $F(2, 144) = 11.53$, $p < .001$, $\eta_p^2 = .14$, but no effect of environment, $F(2, 144) = .33$, $p = .57$, $\eta_p^2 = .002$, or Environment × Age group interaction, $F(2, 144) = 1.06$, $p = .35$, $\eta_p^2 = .02$. We also conducted separate ANOVAs with each search variable as the dependent variable across all seven blocks of the experiment. The results closely match those for the first half of the experiment.

In sum, we found small effects of age on the total amount of information searched but larger effects concerning the patterns of search. The analyses concerning the pattern of information search support the attention allocation hypothesis, which holds that younger children have difficulties using strategies that require selective attention to information and instead rely on spatial strategies to search for information.

Strategy Classification

We classified each participant as selecting either the noncompensatory TTB or the compensatory WADD and Tally strategies in the first, fourth, and final blocks of the decision task. Strategy choices were determined based on the cue values in each trial and the cues' validities. Cue values were coded as either positive (1) or negative (0) so that these numbers can be directly compared, as in the case of TTB, or multiplied by cue validities (ranging from 0 to 1), and added up to obtain weighted sums, as in the case of WADD and Tally. The classification consisted of labeling a participant as a user of the best fitting strategy in each block, where fit was defined as the likelihood of a strategy producing the individual's sequence of choices. Specifically, the model fit was determined as $G^2 = -2\sum \ln(p)$, where p is the probability of making the observed choice.

We implemented a naïve error theory by assuming that each participant deviated from a strategy's prediction and thus made an error with a constant probability. For each participant, we selected the error probability that maximized the likelihood of the data given the strategy. Thus, if a participant made an application error with a constant probability of .20, then the choice of TTB was predicted with a probability of .80 and the other two options were predicted to be chosen with a constant probability of .10. The fits of the best fitting strategy were superior to those expected by chance for all participants, suggesting that the three strategies provide adequate descriptions of their decision behavior.

Figure 2 shows the percentage of participants classified as TTB, WADD, and Tally users in the two environments for the first, fourth, and final

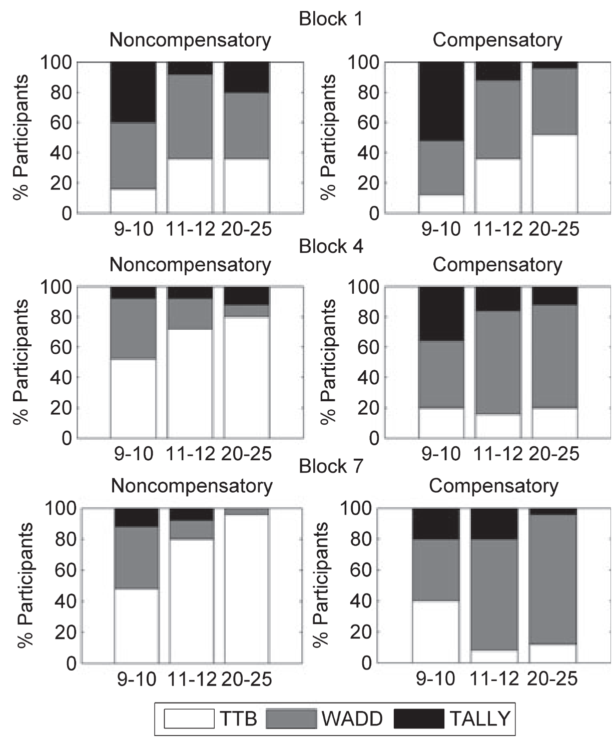

Figure 2. Strategy classification as a function of environment (noncompensatory, compensatory) and block (first, fourth, and seventh) for the three age groups (9–10, 11–12, and 20–25 years old). TTB = take the best; WADD = weighted-additive strategy.

blocks of the decision task. Figure 2 illustrates that in the first block a majority of participants were classified as selecting compensatory strategies regardless of the environment, $\chi^2(1, N = 150) = 0.32$, $p = .85$, $w_{ES} = .05$. Interestingly, younger children were more likely to rely on a simpler compensatory strategy, Tally, relative to older children and adults, suggesting younger children had more difficulties applying the complex WADD strategy.

At the end of the fourth decision block there were clear differences between environments, $\chi^2(1, N = 150) = 37.23$, $p < .001$, $w_{ES} = .45$: As expected, in the noncompensatory environment, TTB better captured participants' decisions, while in the compensatory environment most participants selected compensatory strategies. Additionally, the classification analysis suggested age-related differences in strategy selection similar to the age-related differences in payoff: The 9- to 10-year-olds seem to have had more difficulties in learning to select the appropriate strategy as a function of performance feedback: The effect size (w_{ES}) of environment on strategy classification for the 9- to 10-year-olds was smaller ($w_{ES} = .37$) compared to 11- to 12-year-olds ($w_{ES} = .49$) and adults ($w_{ES} = .54$). Note that younger children generally relied more on the simpler Tally strategy relative to the older groups. This suggests that younger children may have difficulties in relying on the more complex WADD strategy that requires the integration of cue values with their validities and thus preferred the simpler Tally strategy that uses equal weighting of cues.

Finally, the classification results for the final block of the noncompensatory environment show that while the overwhelming majority of young adults learned to select TTB, children, in particular 9- to 10-year-olds, had difficulties in learning to select this strategy even after extensive learning. Concerning the compensatory environment, there was an increase in the number of younger children classified as using TTB compared to the fourth block, possibly due to children getting tired over time.

Strategy Selection Learning

To analyze the reasons underlying age-related differences in strategy selection we modeled participants' choices with the strategy selection learning (SSL) theory (Rieskamp & Otto, 2006). SSL is a computational learning model that decomposes participants' performances into three components: an initial preference parameter, β, representing the initial preference for the noncompensatory TTB strategy; a learning rate parameter, w, representing the speed of learning; and an error parameter, ε, representing errors in strategy application (see the Appendix for a formal definition). The SSL parameters were optimized separately for each individual by maximizing the likelihood of the observed choices.

Overall, SSL captured participants' learning processes well and had an average fit (G^2) that was better than a pure chance baseline model, which assumes that the participants did not use strategies to make decisions but randomly chose one of the three cars. The baseline model predicted the choice of each of the three alternatives with a probability of 1/3 and had an average fit of $G^2 = -2\sum \ln(p) = 263$ for the first four blocks (120 trials). Figure 3a illustrates that the fit of the SSL theory is better than the baseline model for all participants. In addition, we tested SSL against a number of more stringent baseline models and the successful test of the SSL theory against these suggests that it captured participants' choices well and we can confidently interpret the models' parameters. In the following, we report the results based only on the first four blocks of the experiment to ensure that children becoming tired over the course

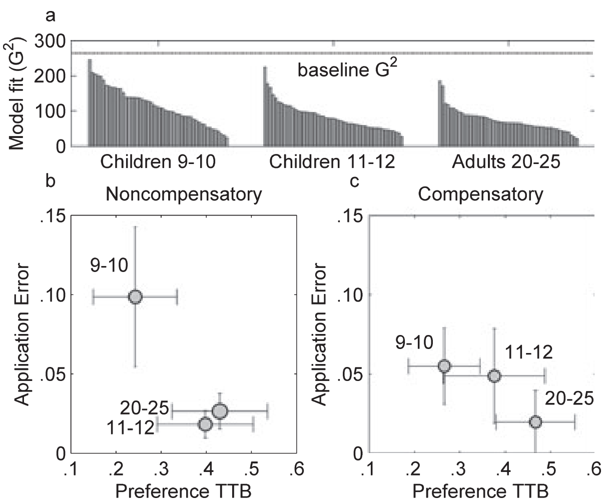

Figure 3. (a) Goodness of fit of the strategy selection learning (SSL) theory for each individual participant. The dotted line represents the baseline G^2 of a pure chance prediction and 0 represents a perfect fit. (b) Participants' parameter values in the noncompensatory and (c) compensatory environments. The location of each circle represents each group's initial preference for take the best (TTB), (β; values below .5 represent preference for weighted-additive [WADD] and Tally), and the proportion of application errors (ε). The diameter of each circle is proportional to the learning parameter (w) with larger circles representing faster learning rates. Error bars represent 95% confidence intervals.

of the study did not influence the results or our conclusions. Nevertheless, the analysis using the full set of blocks provides a similar pattern of results, albeit that age differences are somewhat larger when the full set of blocks is considered.

We first conducted separate ANOVAs with each parameter of the SSL theory as the dependent variable and age group, environment, and their interaction as the independent variables. Figure 3b and c shows the mean estimated parameter values for each of the three age groups and the two environments. Regarding the initial preference parameter, we found an effect of age group, $F(2, 149) = 8.04$, $p < .001$, $\eta_p^2 = .10$, but no effect of environment, $F(1, 149) = .15$, $p = .70$, $\eta_p^2 = .001$, or Age Group × Environment interaction, $F(2, 149) = .22$, $p = .80$, $\eta_p^2 = .003$. As Figure 3 illustrates, the estimated mean value for the initial preference parameter for the noncompensatory strategy TTB was lower for the youngest age group in comparison to the other age groups, illustrating a stronger initial preference for a compensatory strategy. The learning parameter did not differ between age groups, $F(2, 144) = 2.09$, $p = .13$, $\eta_p^2 = .03$, and environments, $F(1, 144) = 0.24$, $p = .62$, $\eta_p^2 < .01$, nor did we find an Age Group × Environment interaction, $F(2, 144) = 0.36$, $p = .69$, $\eta_p^2 < .01$. Finally, concerning the error parameter, children showed significantly more errors when applying strategies, particularly in the noncompensatory environment. We found an effect of age group, $F(2, 144) = 9.13$, $p < .001$, $\eta_p^2 = .11$, and an Environment × Age interaction, $F(2, 144) = 3.09$, $p = .02$, $\eta_p^2 = .05$, but no main effect of environment, $F(1, 144) = 0.35$, $p = .55$, $\eta_p^2 < .01$. As can be seen in Figure 3, 9- to 10-year-olds made more errors overall compared to older children and adults but this was particularly evident in the noncompensatory environment.

As an additional step to understanding differences between age groups with the estimated parameters of the SSL theory, we compared groups in a pairwise fashion. The 9- to 10-year-olds revealed parameter values that differed considerably from those of older children and adults. Separate ANOVAs with each parameter as the dependent variable and age group, environment, and their interaction as the independent variables showed that, compared to adults, 9- to 10-year-olds showed less overall initial reliance on TTB, $F(1, 99) = 17.50$, $p < .001$, $\eta_p^2 = .15$; a slower learning rate, $F(1, 99) = 3.71$, $p = .05$, $\eta_p^2 = .04$; and more application errors, $F(1, 99) = 14.13$, $p < .001$, $\eta_p^2 = .13$. The differences between 9- to 10-year-olds and 11- to 12-year olds were less pronounced: Nonetheless, 9- to 10-year-olds showed a significant tendency for less initial reliance on TTB, $F(1, 99) = 7.01$, $p = .01$, $\eta_p^2 = .07$, and more application errors, $F(1, 99) = 8.25$, $p < .01$, $\eta_p^2 = .08$, but a similar learning rate, $F(1, 99) = 2.04$, $p = .16$, $\eta_p^2 = .02$, compared to older children. We also found an Age × Environment interaction concerning application errors, $F(1, 99) = 6.05$, $p = .01$, $\eta_p^2 = .06$, again suggesting younger children had more difficulties in applying strategies correctly in the noncompensatory environment. A similar analysis comparing the 11- to 12-year-olds and adults revealed no significant age-related differences in initial preference for TTB, $F(1, 99) = 1.48$, $p = .23$, $\eta_p^2 = .02$, and learning rate, $F(1, 99) = 0.29$, $p = .59$, $\eta_p^2 < .01$, nor application errors, $F(1, 99) = 1.01$, $p = .32$, $\eta_p^2 = .01$. Summing up, SSL suggests there are significant age-related differences in strategy selection. While 11- to 12-year-olds resembled adults in their strategy use, 9- to 10-year-olds showed comparatively less reliance on noncompensatory strategies, generally poorer learning, and considerably more application errors, particularly in the noncompensatory environment.

The SSL parameters can help explain the reasons underlying age-related payoff differences. We conducted a hierarchical regression analysis on payoff with age as a predictor (Step 1) and, in a second step, with age and the three SSL parameters as predictors (Step 2). As shown in Table 2, the SSL parameters captured the age differences in payoff quite well in both environments. The regression models captured 89% of the variance in the noncompensatory environment and 79% in the compensatory environment. Age was a significant predictor of performance when entered alone in the regression (Step 1), but it showed a small, nonsignificant relation to payoff when the SSL parameters were examined (Step 2). This analysis shows that the age-related differences can be explained by learning differences that are captured by the parameters of the SSL theory. Although all parameters significantly contributed to payoff, in the noncompensatory environment, initial preference for TTB (β) was the strongest predictor followed by application error (ε). This pattern was reversed in the compensatory environment. The full pattern of results holds even when controlling for individual differences in cognitive abilities, suggesting that our measures of verbal knowledge, speed of processing, and short-term memory did not capture the abilities underlying the age-related parameter differences. Future studies using a more powerful and extensive battery of measures as well as larger sample sizes may be necessary to adequately assess relations between individual

Table 2

Summary of Hierarchical Regression Analysis With Payoff as the Dependent Variable and Age, SSL Parameters, and Cognitive Abilities as Independent Variables for the Noncompensatory and Compensatory Environments

Variable	B	t	p
Noncompensatory environment (N = 75)			
Step 1			
Age	.40	3.77	< .01
Step 2			
Age	.07	1.61	.11
w	−.29	6.59	< .01
β	.65	15.08	< .01
ε	−.41	9.29	< .01
Compensatory environment (N = 75)			
Step 1			
Age	.15	2.63	.01
Step 2			
Age	.15	1.25	.22
w	−.44	7.34	< .01
β	−.49	8.28	< .01
ε	−.61	10.26	< .01

Note. For Step 2, R^2 = .89 in the noncompensatory environment and R^2 = .79 in the compensatory environment. SSL = strategy selection learning; w = learning rate; β = initial preference for take-the-best; ε = error.

differences in cognitive abilities and strategy selection learning. In sum, the regression analysis is consistent with the idea that age-related differences in adaptive strategy selection stem partly from children's initial preference for compensatory strategies but also from problems in correctly executing both compensatory and noncompensatory decision strategies.

Discussion

What decision strategies are available to children? We addressed this question in an experiment in which 9- to 10-year-olds, 11- to 12-year-olds, and adults encountered two different environments and were given extensive opportunity to learn to select the appropriate strategy: One environment favored the use of an information-intensive, compensatory strategy, while the other favored the use of a noncompensatory strategy that neglects information. Our results showed that 11- to 12-year-olds were remarkably similar to adults in their strategy use, both regarding the strategies initially selected and the efficiency in their application. In contrast, 9- to 10-year-olds showed considerably less reliance on noncompensatory strategies, poorer learning, and more application errors, which led to poorer performance compared to older groups, particularly in the noncompensatory environment.

Implications for Understanding the Development of Strategy Selection

Our finding that strategy application errors are more prevalent at younger ages is intuitive and mirrors results from other developmental studies in domains, such as arithmetic skill, estimation, and memory (e.g., Lemaire & Lecacheur, 2002; Luwel, Lemaire, & Verschaffel, 2005; Miller, 1990; Siegler, 1999). The idea that strategies can be misapplied leading to poor performance has a tradition in the developmental literature under the term ''utilization deficiency'' (Miller, 1990). For example, Bjorklund, Miller, Coyle, and Slawinski (1997) have used the concept to explain how the use of memory strategies does not necessarily lead to memory enhancement in children—children may rely on an appropriate memory strategy but fail to apply it correctly. Our results thus match work showing that the optimization of strategy application, for example, in the memory domain, continues to develop after childhood (Shing, Werkle-Bergner, Li, & Lindenberger, 2008).

In turn, the finding that young children performed worse in the noncompensatory compared to the compensatory environment is novel and counterintuitive, particularly when considering that the application of an information-frugal strategy should be well suited to children's working memory limitations. Our findings shed light on why it sometimes could be more difficult for children to apply noncompensatory strategies compared to information-intensive, compensatory ones. We found that although children and adults searched for similar amounts of information, most adults searched for information in order of validity, which allowed them to focus on the relevant pieces. In contrast, younger children searched more often in order of display, making it difficult to focus their attention on the most relevant information. This finding supports the attention allocation hypothesis, which holds that young children have difficulties in selectively attending to the most relevant pieces of information (Davidson, 1991a, 1991b, 1996; Miller, Haynes, DeMarie-Dreblow, & Woody-Ramsey, 1986; Turner & Bentley, 1982). The ability to distinguish between relevant and irrelevant information seems to develop throughout adolescence and may have significant real-world consequences. For example, Cook and Rieser (2005) showed that individual differences in this ability persist into adolescence and predict achievement in mathematical problem solving.

Our results also suggest that the use of compensatory strategies is not trivial for 9- to 10-year-olds, as they showed increased reliance on Tally, a simpler, unit-weighted version of WADD, compared to older groups. This suggests that the younger children had difficulties in integrating cue values with their validities and that the ability to integrate information in working memory is also related to the children's efficient application of strategies: WADD requires decision makers to hold in mind both cue values and cue weights posing additional memory and processing requirements compared to Tally.

In sum, our results suggest that the efficient execution of noncompensatory and compensatory strategies pose significant demands to children but the two may follow slightly different developmental paths. Noncompensatory strategies rely mainly on the ability to selectively attend to the most relevant information, which can be mastered at levels close to adult performance only at age 11. In contrast, simple compensatory strategies that do not require differential cue weighting seem to be in reach of children as young as 9. While our cross-sectional design is only indicative of such a pattern, future studies making use of a longitudinal design could map the developmental path of the use of compensatory and noncompensatory strategies more directly as well as individual differences in both cognitive ability and other factors, such as formal education, on strategy selection.

Computational Models of Strategy Selection

In the present study, we chose to use a computational model of strategy selection, SSL theory (Rieskamp, 2006, 2008; Rieskamp & Otto, 2006), to describe children's and adults' strategy selection processes. SSL provides a parsimonious model that has been specifically designed and successfully tested to explain SSL in the domain of probabilistic inferences. Our findings suggest that SSL is useful in identifying which decision components (e.g., utilization deficits) develop across late childhood to allow adaptive strategy selection. Nevertheless, future studies should test SSL against other qualitatively different approaches and models (e.g., Rieskamp, 2006; Shrager & Siegler, 1998) to assess whether further assumptions are useful in accounting for the differences between children and adults' decision-making processes.

Improving Strategy Application

Our results suggest that children had difficulties in selecting decision strategies as a function of the situation despite receiving extensive performance feedback. Future studies should look at the factors favoring children's ability to correctly apply decision strategies. For example, future research could use the choice versus no-choice method (Lemaire & Siegler, 1995) to investigate whether explicit training of noncompensatory strategies can lead to examining less irrelevant information or weighting information appropriately. Another promising technique involves having children rely on well-known, self-generated cue rankings, to encourage 9- to 10-year-olds to focus on the most relevant pieces of information (see Bereby-Meyer et al., 2004; Montanelli, 1972). In addition, it may be fruitful to adopt experimental designs that require participants to rely on recalled cues from memory, as opposed to observing cues on a computerized display, to test whether these more demanding situations can lead children to rely on simpler noncompensatory strategies (e.g., Bröder & Schiffer, 2003; Persson & Rieskamp, 2009). Hopefully, such work will help generate interventions with the power to improve children's real-world decisions, from food choice to crossing the street.

Conclusion

We investigated children's learning ability to select the most successful strategy in different decision environments. Our results suggest that specific decision strategies exploit abilities that pose different but significant challenges to young children: Simple noncompensatory strategies require selective attention to information, while compensatory strategies have considerable information-integration requirements. Crucially, our results show that 9- to 10-year-olds prefer information-intensive strategies, and have a harder time learning to select frugal noncompensatory strategies even when given substantial learning opportunity. Thus, younger children do not seem to benefit from the reduced informational load of noncompensatory strategies that are usually considered computationally simpler. In other words, for younger children, easy may come hard.

References

Bereby-Meyer, Y., Assor, A., & Katz, I. (2004). Children's choice of strategies: The effects of age and task demands. *Cognitive Development*, *19*, 127–146.

Bjorklund, D. F., Miller, P. H., Coyle, T. R., & Slawinski, J. L. (1997). Instructing children to use memory strategies: Evidence of utilization deficiencies in memory training studies. *Developmental Review*, *17*, 411–441.

Bröder, A., & Schiffer, S. (2003). ''Take the best'' versus simultaneous feature matching: Probabilistic inferences from memory and effects of representation format. *Journal of Experimental Psychology: General*, *132*, 277–293.

Bunge, S., & Zelazo, P. D. (2006). A brain-based account of the development of rule use in childhood. *Current Directions in Psychological Science*, *15*, 118–121.

Case, R. (1985). *Intellectual development: Birth to adulthood*. New York: Academic Press.

Cook, J. L., & Rieser, J. J. (2005). Finding the critical facts: Children's visual scan patterns when solving story problems that contain irrelevant information. *Journal of Educational Psychology*, *97*, 224–234.

Crone, E. A., & Van der Molen, M. W. (2007). Development of decision-making in school-aged children and adolescents: Evidence from heart rate and skin conductance analysis. *Child Development*, *78*, 1288–1301.

Czienskowski, U. (2004). The Oil Drilling Experiment [Computer software]. Berlin, Germany: Max Planck Institute for Human Development.

Davidson, D. (1991a). Children's decision-making examined with an information-board procedure. *Cognitive Development*, *6*, 77–90.

Davidson, D. (1991b). Developmental differences in children's search of predecisional information. *Journal of Experimental Child Psychology*, *52*, 239–255.

Davidson, D. (1996). The effect of decision characteristics on children's selective search of predecisional information. *Acta Psychologica*, *92*, 263–281.

Diamond, A. (2001). Prefrontal cortex development and development of cognitive functions. In N. J. Smelser & P. B. Baltes (Eds.), *International encyclopedia of the social and behavioral sciences* (pp. 11976–11982). Oxford, UK: Pergamon.

Dieckmann, A., & Rieskamp, J. (2007). The influence of information redundancy on probabilistic inferences. *Memory and Cognition*, *35*, 1801–1813.

Ford, J. K., Schmitt, N., Schechtman, S. L., Hults, B. M., & Doherty, L. (1989). Process tracing methods: Contributions, problems, and neglected research questions. *Organizational Behavior and Human Decision Processes*, *43*, 75–117.

Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*, 650–669.

Gregan-Paxton, J., & Roedder John, D. (1995). Are young children adaptive decision makers? A study of age differences in information search behavior. *Journal of Consumer Research*, *21*, 567–579.

Gregan-Paxton, J., & Roedder John, D. (1997). The emergence of adaptive decision making in children. *Journal of Consumer Research*, *24*, 43–56.

Hayes, B., McKinnon, R., & Sweller, N. (2008). The development of category-based induction: reexamining conclusions from the induction then recognition (ITR) paradigm. *Developmental Psychology*, *44*, 1430–1441.

Hoffrage, U., Weber, A., Hertwig, R., & Chase, V. M. (2003). How to keep children safe in traffic: Find the daredevils early. *Journal of Experimental Psychology: Applied*, *9*, 249–260.

Hooper, C. J., Luciana, M., Conklin, H. M., & Yarger, R. S. (2004). Adolescents' performance on the Iowa Gambling Task: Implications for the development of decision making and ventromedial prefrontal cortex. *Developmental Psychology*, *40*, 1148–1158.

Howse, R. B., Best, D. L., & Stone, E. R. (2003). Children's decision making: The effects of training, reinforcement, and memory aids. *Cognitive Development*, *18*, 247–268.

Kail, R. (1991). Developmental change in speed of processing during childhood and adolescence. *Psychological Bulletin*, *109*, 490–501.

Kail, R., & Salthouse, T. A. (1994). Processing speed as a mental capacity. *Acta Psychologica*, *86*, 199–225.

Klaczynski, P. A. (2001). Analytic and heuristic processing influences on adolescent reasoning and decision-making. *Child Development*, *72*, 844–861.

Klahr, D., Fay, A. Y., & Dunbar, K. (1993). Heuristics for scientific experimentation: A developmental study. *Cognitive Psychology*, *25*, 111–146.

Klayman, J. (1985). Children's decision strategies and their adaptation to task characteristics. *Organizational Behavior & Human Decision Processes*, *35*, 179–201.

Kuhn, D., Iordanou, K., Pease, M., & Wirkala, C. (2008). Beyond control of variables: What needs to develop to achieve skilled scientific thinking? *Cognitive Development*, *23*, 435–451.

Lafon, P., Chasseigne, G., & Mullet, E. (2004). Functional learning among children, adolescents, and young adults. *Journal of Experimental Child Psychology*, *88*, 334–347.

Lehrl, S. (1999). *Mehrfachwahl-Wortschatz-Intelligenztest: Manual mit Block MWT-B*. Balingen, Germany: Spitta.

Lemaire, P., & Lecacheur, M. (2002). Applying the choice/no-choice methodology: The case of children's strategy use in spelling. *Developmental Science*, *5*, 43–48.

Lemaire, P., & Siegler, R. S. (1995). Four aspects of strategic change: Contributions to children's learning of multiplication. *Journal of Experimental Psychology: General*, *124*, 83–97.

Luwel, K., Lemaire, P., & Verschaffel, L. (2005). Children's strategies in numerosity judgment. *Cognitive Development*, *20*, 448–471.

Mata, R., Schooler, L., & Rieskamp, J. (2007). The aging decision maker: Cognitive aging and the adaptive selection of decision strategies. *Psychology and Aging*, *22*, 796–810.

Miklich, D. R., & Gillis, J. S. (1975). Interaction of age and cue validities in multiple-cue probability learning by children. *Psychological Reports*, *37*, 235–240.

Miller, P. H. (1990). The development of strategies of selective attention. In D. F. Bjorklund (Ed.), *Children's strategies: Contemporary views of cognitive development* (pp. 157–184). Hillsdale, NJ: Erlbaum.

Miller, P. H., Haynes, V. F., DeMarie-Dreblow, D., & Woody-Ramsey, J. (1986). Children's strategies for gathering information in three tasks. *Child Development*, *57*, 1429–1439.

Montanelli, D. S. (1972). Multiple-cue learning in children. *Developmental Psychology*, *3*, 302–312.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge, UK: Cambridge University Press.

Persson, M., & Rieskamp, J. (2009). Inferences from memory: Strategy- and exemplar-based judgment models compared. *Acta Psychologica*, *130*, 25–37.

Reyna, V. F., & Farley, F. (2006). Risk and rationality in adolescent decision making: Implications for theory, practice, and public policy. *Psychological Science in the Public Interest*, *7*, 1–44.

Rieskamp, J. (2006). Perspectives of probabilistic inferences: Reinforcement learning and an adaptive network compared. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, *32*, 1371–1384.

Rieskamp, J. (2008). The importance of learning when making inferences. *Judgment and Decision Making*, *3*, 261–277.

Rieskamp, J., & Hoffrage, U. (2008). Inferences under time pressure: How opportunity costs affect strategy selection. *Acta Psychologica*, *127*, 258–276.

Rieskamp, J., & Otto, P. (2006). SSL: A theory of how people learn to select strategies. *Journal of Experimental Psychology: General*, *135*, 207–236.

Schauble, L. (1996). The development of scientific reasoning in knowledge-rich contexts. *Developmental Psychology*, *32*, 102–119.

Scheibehenne, B., Miesler, L., & Todd, P. M. (2007). Fast and frugal food choices. Uncovering individual decision heuristics. *Appetite*, *49*, 578–589.

Shing, Y. L., Werkle-Bergner, M., Li, S.-C., & Lindenberger, U. (2008). Associative and strategic components of episodic memory: A life-span dissociation. *Journal of Experimental Psychology: General*, *137*, 495–513.

Shrager, J., & Siegler, R. S. (1998). SCADS: A model of children's strategy choices and strategy discoveries. *Psychological Science*, *9*, 405–410.

Siegler, R. S. (1999). Strategic development. *Trends in Cognitive Sciences*, *3*, 430–435.

Sloutsky, V., Lo, Y. F., & Fischer, A. V. (2001). How much does a shared name make things similar? Linguistic labels, similarity, and the development of inductive inference. *Child Development*, *72*, 1695–1709.

Turner, I. F., & Bentley, G. (1982). Irrelevant information: Some effects on children's problem-solving. *Contemporary Educational Psychology*, *7*, 41–49.

von Helversen, B., Mata, R., & Olsson, H. (2010). Do children profit from looking beyond looks? From similarity-based to cue-abstraction processes in multiple-cue judgment. *Developmental Psychology*, *46*, 220–229.

Wechsler, D. (1981). *Wechsler Adult Intelligence Scale: Revised manual (WAIS–R)*. New York: Psychological Corporation.

Zimmerman, C. (2007). The development of scientific thinking skills in elementary and middle school. *Developmental Review*, *27*, 172–223.

Appendix

Computational Specification of the Strategy Selection Learning (SSL) Theory

The SSL theory (Rieskamp & Otto, 2006) assumes that a person has subjective expectancies associated with each decision strategy, selects strategies proportional to their expectancies, and updates expectancies on the basis of feedback. We assume that the strategy repertoire can be reduced to three strategies: take the best (TTB), Tally, and weighted additive (WADD). An individual's preference for a strategy i is expressed by positive expectancies $q(i)$. The probability that strategy i is selected at trial t depends on its expectancy relative to the other strategies' expectancies and is defined by

$$p_t(i) = \frac{q_t(i)}{\sum_{j=1}^{N} q_t(j)}. \tag{A1}$$

The strategies' expectancies in the first period of the task may differ and are defined by

$$q_1(i) = r_{\max} \cdot w \cdot \beta_i, \tag{A2}$$

where $r_{\max}$ is the maximum payoff that can be obtained by a correct decision, w is the initial association parameter (constrained by $w > 0$), and β is the initial preference parameter (restricted to $0 < \beta < 1$ and $\sum_{i=1}^{N} \beta_i = 1$). The initial association parameter expresses a person's initial association with the available strategies relative to later reinforcement and can thus be interpreted as the learning rate at which individuals adapt their strategy selection throughout the task. To keep our model parsimonious, we assumed an equal initial preference parameter β_i for Tally and WADD (i.e., $\beta_{\text{Tally}} = \beta_{\text{WADD}}$), so that a value of $\beta_{\text{TTB}} = .40$ implies a value for $\beta_{\text{Tally}} = \beta_{\text{WADD}} = .30$. Consequently, $\beta > 1/3$ implies that the decision maker will select TTB with a larger probability at the beginning of the task than Tally or WADD.

After a decision is made, the expectancies of the cognitive strategies are updated for the next trial t by

$$q_t(i) = q_{t-1}(i) + I_{t-1}(i) \cdot r_{t-1}(i), \tag{A3}$$

where $r_{t-1}(i)$ is the reinforcement defined by the produced payoff of a strategy and $I_{t-1}(i)$ is an indicator function that denotes whether a strategy has been selected. The indicator function $I_{t-1}(i)$ equals 1 if strategy i was selected and equals 0 if the strategy was not selected. According to SSL, two requirements are necessary to assume that a strategy was selected on any given trial: (a) the necessary information for applying the strategy was acquired, and (b) the choice coincides with the strategy's prediction.

The SSL theory incorporates a simple error theory to account for application errors. The probability $p(a \mid i)$ of choosing alternative a when strategy i is selected is either $p(a \mid i) = 1$ or $p(a \mid i) = 0$ for deterministic strategies (if strategies lead to an ambiguous prediction $p(a \mid i) = 1/k$, with k being the number of alternatives the strategy does not discriminate between). The conditional probability of choosing alternative a given application error ε is

$$p_t(a|i, \varepsilon) = (1 - \varepsilon) \cdot p_t(a|i) + \frac{\varepsilon}{k-1} \cdot p_t(\bar{a}|i), \tag{A4}$$

where $p_t(\bar{a}|i)$ denotes the probability of choosing any other alternative than a out the available alternatives, given strategy i was selected. Finally, the probability of choosing alternative a depends on the probabilities of selecting the strategies and the corresponding choice probabilities of the strategies

$$p_t(a) = \sum\nolimits_{i=1}^{N} p_t(i) \cdot p_t(a|i, \varepsilon). \tag{A5}$$