Learning to Choose:

Cognitive Aging and Strategy Selection Learning in Decision Making

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Abstract

Decision makers often have to learn from experience. In these situations, people must use the available feedback to select the appropriate decision strategy. How does the ability to select decision strategies on the basis of experience change with age? Younger and older adults’ strategy selection learning was examined in a probabilistic inference task using a computational model of strategy selection learning. Older adults showed poorer decision performance and had more difficulties learning to adaptively select strategies compared to younger adults. In particular, older adults performed poorly in an environment favoring the use of a more cognitively demanding strategy. The results suggest that the impact of cognitive aging on strategy selection learning depends on the structure of the decision environment.

Keywords: aging; decision making; learning; strategy selection; adaptive

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Alan Greenspan was Chairman of the Federal Reserve and thus one of the most important decision makers in American economic policy for almost 20 years, from his early 60s to his late 70s. Greenspan represents an example of how the ability of older adults to make sound financial choices is becoming an increasingly relevant topic as more and more people are asked to make important decisions well into old age. Successful problem solving and decision making depend crucially on the individual’s ability to adapt his or her behavior or strategy to a particular situation. The idea that people have a repertoire of strategies and can adapt their selection to different problem structures or environments is common in the developmental (Siegler, 1999) and decision-making literatures (Gigerenzer, Todd, & the ABC Research Group, 1999; Payne, Bettman, & Johnson, 1993). However, we still lack knowledge about older adults’ ability to learn to select different types of strategies.

Compensatory and Noncompensatory Decision Strategies

When choosing stocks for a portfolio many different pieces of information (i.e., cues) are available to investors, such as the stocks’ cost, past performance, and so on. One type of strategy that can be used to choose between stocks is a compensatory strategy, such as a weighted-additive rule (WADD; e.g., Payne, Bettman, & Johnson, 1993). Compensatory strategies allow a cue with negative information, for example, a stock’s poor performance in the previous year, to be compensated by one or more cues with positive information, for example, low cost. In other words, a compensatory strategy allows trade-offs between positive and negative information. The weighted-additive rule (WADD) is a prototypical example of a compensatory strategy and integrates all available information by adding cue values (e.g., performance, cost) weighted by their importance. A less cognitively demanding compensatory strategy may assign equal weights to cues and add them to reach a decision (TALLY; Gigerenzer & Goldstein, 1996). In contrast, an investor may rely on an information-frugal, noncompensatory strategy, such as TTB (TTB; Gigerenzer & Goldstein, 1996), which focuses on the single most important cue, cost, to make a decision. If the most important cue does not discriminate between the options, the second most important cue, say past performance, is considered, and so on until a decision is made. This strategy is called noncompensatory because less
important cues (e.g., past performance) cannot overrule a more important cue such as cost. Whether a strategy will successfully select the best option (i.e., the stock that leads to the largest profit) depends on the structure of the environment, specifically, the association between the cues (e.g., cost, past performance) and the criterion (profit), as well as the correlation between cues. Dieckmann and Rieskamp (2007) have shown that the strategies’ performance depend on the degree of redundancy of information. In a situation with low information redundancy, that is, when the cues are not correlated with each other and each cue offers some valid information, a compensatory strategy is best. In contrast, in a situation of high information redundancy, when 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.

Findings from research on arithmetic skill suggests that older adults are overall adaptive in choosing appropriate strategies as a function of the problem type, albeit less so than younger adults (e.g., Lemaire, Arnaud, & Lecacheur, 2004. Likewise, initial findings on decision making suggest that older adults are able to select appropriate strategies as a function of environment structure but are more likely to rely on simpler strategies, compared to younger adults due to age-related cognitive decline (Mata, Schooler, & Rieskamp, 2007; Pachur, Mata, & Schooler, in press). For example, Mata et al. gave participants detailed descriptions of two decision environments and observed that both younger and older adults selected simpler strategies, such as TTB, in the appropriate environment, that is, when some information was not informative about the value of options. Nevertheless, more older than younger adults were classified as using strategies that ignored available information regardless of whether the environment favored this type of strategy. This suggests that older adults have more difficulties relying on cognitively demanding strategies such as WADD. Decision makers are often not provided with detailed descriptions of a decision environment but instead have to learn the characteristics of the situation from experience. In this article we investigate how younger and older adults differ in their learning to select decision strategies as a function of the environment.
Learning to Choose

Younger adults are often able to quickly learn which strategies are successful in solving a particular problem as a function of feedback (Dieckmann & Rieskamp, 2007; Rieskamp, 2006, 2008; Rieskamp & Otto, 2006; but see Bröder & Schiffer, 2006). For example, Rieskamp and Otto asked younger adults to infer which of two objects scored higher on a criterion on the basis of several cues and observed that the overwhelming majority of young adults were able to adaptively select, as a function of performance feedback, either TTB, or WADD.

Research examining the impact of aging on learning and decision making suggests that older adults have problems learning the value of cues (Chasseigne, et al., 2004) and options (e.g., Denburg, Recknor, Bechara, & Tranel, 2006; Marschner et al., 2005; Samanez-Larkin et al., 2007; Wood, Busemeyer, Koling, Cox, & Davis, 2005). Wood and colleagues asked younger and older adults to play a version of the Iowa Gambling Task, in which people learn on the basis of outcome feedback which of several options produces on average the largest payoff, and found no age differences in terms of overall performance scores (for a similar result see Kovalchick, Camerer, Grether, Plott & Allman, 2005). However, computational modeling of participants’ decision making suggested that older adults had more trouble learning the value of options due to more rapid forgetting, as well as motivational changes in increased attention to monetary gains as opposed to losses compared to younger adults. In sum, in addition to differences in initial strategy preferences (Mata et al., 2007; Pachur et al., in press) younger and older adults may additionally differ in their ability to learn from feedback (e.g. Wood et al., 2005).

Our study extends the work on aging and learning in decision making by assessing how aging impacts the ability to learn the values of strategies. Our main interest was to evaluate the ability of younger and older adults to go beyond their initial strategy preferences and adapt their strategy use as a function of performance feedback in a probabilistic inference task. We specifically investigated how differences in various components of decision making, such as initial strategy preferences, general learning deficits, and strategy application errors simultaneously contribute to adaptive
decision making. We were particularly interested in knowing whether older adults’ adaptivity through learning depended on the structure of the environment, namely, whether older adults would be better at learning to select the simpler TTB, in comparison to the information-intensive WADD strategy. For this purpose, we relied on a computational modeling approach that allowed us to assess how younger and older adults adaptivity depended on the different components of interest, namely, initial strategy preferences, learning, and strategy application errors.

In our decision making task participants were asked to repeatedly infer which of three stocks would have the larger revenue based on six cues such as the international standing or liquidity of the companies that the stock represented. To study the ability to adaptively select strategies we asked participants to make decisions in either an environment favoring the use of the simple, noncompensatory strategy TTB strategy (noncompensatory environment) or one favoring the information-intensive, compensatory WADD strategy (compensatory environment).

Method

Participants

Fifty younger adults (mean age = 24.1 years, SD = 3.9, range = [19,34]; 54% females) and 50 older adults (mean age = 69.0 years, SD = 3.6, range = [60,79]; 58% females) participated in the study. The majority of younger adults were students at the Free University of Berlin (mean years of education: 16.3, SD = 2.5). Older adults were community-dwelling adults recruited from newspaper ads (mean years of education: 15.8, SD = 3.5). Participants were paid according to their performance in the decision task and earned €0.10 for each correct decision and paid €0.05 for each incorrect decision.

Design

The experimental design had three factors: environment (between subjects; compensatory vs. noncompensatory), trial block (within subject; 1 to 7), and age group (younger vs. older).

Material

We designed an environment in which the WADD strategy performed best (compensatory
environment) and one in which the TTB strategy performed best (non-compensatory environment). The cues in both environments had similar validities so that participants could not simply infer the best strategy by the distribution of the cue validities (for such a study see Mata et al., 2007). In contrast, in order to find the best strategy the participants had to learn on the basis of outcome feedback how the strategies performed.

The environments were constructed so that each participant of a given age group observed a slightly different set of decision items but age groups were matched regarding the items sets (yoked design). Specifically, we constructed 25 noncompensatory environments (one environment per participant within an age group) by creating 25 sets of 30 decision items. Each of the sets of 30 decision items were constituted by 3 options that varied on 6 cues of binary value (representing a positive or negative value of each option on the given cue). Each set of 30 decisions was constructed such that the average accuracy of the strategies defined as the proportion of correct decisions when following the strategies predictions was 90%, 60%, and 60%, for TTB, TALLY, and WADD, respectively. We also constructed 25 compensatory environments by creating 25 sets of 30 decision items in which the average accuracy of strategies was reversed with 60%, 77%, and 90% , for TTB, TALLY, and WADD, respectively. In each environment, the 30 items were repeatedly presented to participants in seven blocks, with a random presentation order of the 30 items within each block. Feedback was provided after the first block to allow learning. Overall, the three strategies made different predictions for about a third of the items in both the noncompensatory and compensatory environments. Because each participant observed a slightly different environment, the cue validities varied slightly between participants. Cue validities refer to the accuracy of a cue, that is how often one would make a correct decision when relying on this cue. For instance, a cue with a validity of 70% would lead to a correct decision in 70 of 100 decisions in which the cue recommends a specific choice. The average cue validities were the following for the noncompensatory environment: 82%, 67%, 58%, 50%, 42%, 36%, and for the compensatory environment: 72%, 65%, 58%, 50%, 43%, 36%.
We wanted to assign labels to each cue such that labels would match participants’ perceptions of each cue’s validity. For this purpose, we constructed two sets of six cues labels differing in the dispersion of cue validity obtained from importance ratings of an additional independent sample of 73 younger and older adults. We thus obtained a dispersed noncompensatory set of labels (expert ratings, political stability, revenue, stock ratings, liquidity, comparison to an index with average ratings of 3.9, 3.4, 3.4, 3.1, 2.6, and 2.2 on a scale from -7 to +7, respectively) and a less dispersed compensatory set (expert ratings, cost/gain ratio, international company, political stability, revenue, stock ratings, with average ratings of 3.9, 3.6, 3.6, 3.4, 3.4, and 3.1, respectively). We thus aimed to have perceived cue importance reflect the actual cue validities provided to the participants during the experiment. All cues were given dichotomous values: For example, a stock could have either a “very good” or an “average” rating from its shareholders; or perform “better than” or “equal to” the index average.

Procedure

Participants were asked to make decisions about which of three stocks would be more profitable in a year’s time on the basis of the stocks’ characteristics (i.e., cues). The cues, which of the cue values indicated higher profits, and the concept of cue validity were explained to the participants at the beginning of the decision task. Participants could search for information by clicking on each of the six icons on the top of the screen and were free to decide when to stop search and in which order to click on cues (see Figure 1). The cue validities were visible throughout the task below the icon representing each cue. When a cue was clicked on, the characteristics were revealed for the three stocks 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 blocks in which participants received feedback after a decision had been made, outcome feedback was provided by either a green correct box with a “smiley” or a red incorrect 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–
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symbol substitution and digit span tasks.

Results

In the following, we first report participants’ overall performance by examining their payoffs. We then present participants’ pre-decisional information search as well as describe the strategies they selected. Finally, we present the modeling of participants’ learning process using a computational learning theory.

Payoffs

Overall, payoff results suggest that participants were able to improve their performance on the basis of feedback but older adults showed overall poorer performance compared to younger adults (see Figure 2). In addition, older adults’ had significant difficulties improving their performance on the basis on feedback in the compensatory environment, but benefitted more from feedback in the environment favoring the use of the simpler, TTB strategy.

We conducted a repeated measures analysis of variance with payoffs across the seven blocks as the dependent variable and age group, environment, and their interaction as independent variables. We found main effects of age group, $F(1, 96) = 34.94, p < .001, \eta_p^2 = .27$, and environment, $F(1, 96) = 6.81, p = .01, \eta_p^2 = .07$, but no significant age by environment interaction, $F(1, 96) = 0.32, p = .58, \eta_p^2 < .01$. As can be seen in Figure 2, participants improved their performance across blocks, $F(6, 91) = 17.6, p < .001, \eta_p^2 = .54$, but seem to have improved more across blocks in the noncompensatory compared to the compensatory environment, as we found an interaction between block and environment, $F(6, 91) = 4.03, p < .001, \eta_p^2 = .21$. Concerning age differences in learning, no block by age group interaction emerged, $F(6, 91) = 1.28, p = .27, \eta_p^2 = .08$. However, there was a significant block by environment by age group interaction, $F(6, 91) = 2.76, p = .02, \eta_p^2 = .15$. To further investigate this three-way interaction, we conducted follow-up analysis separately for each environment. We found no block by age group interaction in the noncompensatory environment, $F(6, 43) = 1.91, p = .10, \eta_p^2 = .21$, but we identified a significant block by age group interaction in the compensatory environment, $F(6, 43) = 2.53, p = .04, \eta_p^2 = .26$, suggesting that younger adults
increased their performance more than older adults. Also, when conducting equivalent analyses separately for each environment and age group, we found learning effects in the noncompensatory environment for both the younger, $F(6, 19) = 17.51, p < .001, \eta_p^2 = .85$, and older age groups, $F(6, 19) = 7.39, p < .001, \eta_p^2 = .70$. In the compensatory environment, however, we found learning effects for the younger, $F(6, 19) = 2.98, p = .03, \eta_p^2 = .49$, but not the older age group, $F(6, 19) = 1.77, p = .16, \eta_p^2 = .36$. In sum, while older adults’ improved their performance on the basis of feedback in the noncompensatory environment, they did not benefit from feedback in the environment favoring the more complex WADD strategy.

Information Search

To describe participants’ information search we considered the average proportion of information searched per trial (PROP) and the proportion of trials in which information was searched in the order of the cues’ validities (VALIDITY). The results are summarized in Table 1. Overall, our results suggest that while there were no significant age differences in the total amount of information searched, younger adults tended to search more often according to cue validities compared to older adults.

We conducted separate repeated measures ANOVA for each search variable using the search in each block as dependent variables and age group and environment as independent variables. The results concerning the proportion of information search (PROP) suggest that participants searched for similar amounts of information regardless of environment, block, and age group. The analysis revealed a marginal effect of environment, $F(1, 96) = 2.80, p = .10, \eta_p^2 = .03$), but no effect of age group, $F(1, 96) = 0.09, p = .77, \eta_p^2 < .01$, or an interaction of age group by environment, $F(1, 96) = 0.01, p = .94, \eta_p^2 < .01$. We also found no effect of block, $F(6, 91) = 1.36, p = .24, \eta_p^2 = .08$, or block by age group interaction, $F(6, 91) = 0.43, p = .86, \eta_p^2 = .03$, block by environment interaction, $F(6, 91) = 1.63, p = .15, \eta_p^2 = .10$, or a block by environment by age group interaction, $F(6, 91) = 1.70, p = .13, \eta_p^2 = .10$.

The results concerning the order in which participants searched for cues (VALIDITY) suggest
that younger adults searched more often in order of validity, particularly in the noncompensatory environment. We identified a significant effect of environment, $F(1, 96) = 4.41, p = .04, \eta^2_p = .04$, and an effect of age group, $F(1, 96) = 32.86, p < .001, \eta^2_p = .26$, but no age group by environment interaction, $F(1, 96) = 0.31, p = .58, \eta^2_p < .01$. The analysis revealed an effect of block, $F(6, 91) = 7.26, p < .001, \eta^2_p = .32$, and a block by age group interaction, $F(6, 91) = 2.22, p = .05, \eta^2_p = .13$, but no block by environment interaction, $F(6, 91) = 1.61, p = .15, \eta^2_p = .10$, nor block by environment by age group interaction, $F(6, 91) = 1.02, p = .42, \eta^2_p = .06$. Follow-up analyses conducted separately for the two age groups suggest that younger adults significantly more often searched for the cues in the order of their validities from the first ($M = .34, SD = .35$) to the last block ($M = .66, SD = .44$), $F(6, 43) = 6.63, p < .001, \eta^2_p = .48$, while older adults did not ($M = .10, SD = .20$ vs. $M = .23, SD = .38$), $F(6, 43) = 1.40, p = .24, \eta^2_p = .16$. In sum, while there were no significant changes across blocks in the total amount of information searched nor age differences thereof, younger adults increased their tendency across blocks to search according to the cue validities while older adults did not.

**Strategy Classification**

We investigated which strategies participants relied on to integrate information by classifying each participant as selecting the TTB, TALLY, or WADD strategy. A participant was classified as using a specific strategy when this strategy reached the best fit in predicting the participant’s inferences. The classification was determined for each block, and the fit of a strategy was defined by the likelihood of a strategy producing the individual’s sequence of choices. Specifically, the strategy fit was determined as $G^2 = -2 \sum \ln(p)$, where $p$ is the model’s predicted probability of making the observed choice. $G^2$ is a common measure of fit that is roughly chi-square distributed (Wood et al., 2005) and conveys the ability of a model or strategy to predict each participant’s choices. According to the formula, the probabilities with which a strategy makes each choice are added to obtain $G^2$ for that strategy. If a strategy flawlessly predicted each choice of a participant with a probability of 1, then $G^2$ would be 0. In turn, if the strategy always guessed in the 210 trials, assigning a .3 probability
to each option, $G^2$ would be roughly 446. Consequently, in our classification the strategy with the lowest $G^2$ was assigned to the participant. To obtain probabilistic predictions from each strategy, 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, the probability of an application error was selected such that the likelihood of the data given the strategy was maximized. Thus, if a participant made an application error with a constant probability of .20, then TTB’s choice was predicted with a probability of .80 and the other two options were predicted to be chosen with a probability of .10.

Figure 2 shows the classification results for the two age groups in each block of the experiment in the two environments. In the following, we focus on strategy classification in the first and last blocks of trials because these are most informative concerning 1) initial strategy preferences in the absence of feedback, and 2) strategy selection after considerable learning. Figure 2 illustrates that in the first block the majority of participants were classified as users of a compensatory strategy regardless of the environment, $\chi^2 (2, N = 100) = .17, p = .92, w_{EffectSize} = w_{ES} = .04$. In comparison, at the end of the experiment the results differed depending on the environment, $\chi^2 (2, N = 100) = 61.27, p < .001, w_{ES} = .79$. As expected, in the noncompensatory environment TTB captured participants’ decisions better than a compensatory strategy, whereas in the compensatory environment the compensatory strategy WADD predicted participants’ decisions best. The classification analysis also suggested age-related differences in strategy selection: Fewer older adults were classified as selecting the appropriate strategy at the end of the experiment compared to younger adults, $\chi^2 (1, N = 100) = 12.71, p = .001, w_{ES} = .34$. Finally, there was an effect of environment for the older group in the last block: While the majority of older adults (76%) were classified as selecting the appropriate TTB in the noncompensatory environment, only about half (48%) were classified as selecting WADD in the compensatory environment, $\chi^2 (1, N = 50) = 16.64, p < .001, w_{ES} = .28$.

**Strategy Selection Learning**

One goal of our research was to account for participants’ decision making using a
computational model of strategy selection that distinguishes between different components of the decision process. Specifically, we used the strategy selection learning theory (SSL; Rieskamp & Otto, 2006) to model each participant’s learning processes. Then, by considering age differences in model parameter estimates corresponding to each decision component, we hoped to help explain why older adults performed worse and were less adaptive in selecting decisions strategies as a function of the environment compared to younger adults. According to SSL, the decision maker possesses a repertoire of decision strategies and each strategy has an expectancy that represents the subjective value of the strategy to the decision maker, that is, a belief concerning how well the strategy can be used to tackle the current decision problem. The initial strategy expectancies may differ on the basis of past experience. SSL further assumes that when a person applies a strategy the outcome of the resulting decision will act as reinforcement and change the strategy’s expectancy. Finally, the SSL theory assumes that decision makers sometimes make mistakes, namely, a decision maker may sometimes select a strategy but fail to make a decision in line with the prediction of that strategy which is regarded as a strategy application error.

Model fitting. The calculations corresponding to each of the steps underlying strategy selection learning according to SSL are formalized in the Appendix (see also Rieskamp, 2006, 2008). We used SSL under the assumption that the strategy repertoire consisted of the three strategies of interest, TTB, TALLY, and WADD. The SSL theory allowed us to go beyond mean payoff differences and decompose participants’ strategy selection learning into three components (parameters): the initial strategy preference parameter, $\beta$, representing the initial preference for the TALLY strategy (the most prevalent strategy in the first block of trials according to our strategy classification analysis), an initial association parameter, $w$, representing learning rate, and an error parameter, $\varepsilon$, representing errors in strategy application. The SSL parameters were optimized separately for each participant by maximizing the likelihood of the observed decisions given the appropriate information search is observed for the hypothesized strategy (see Appendix). Overall, SSL captured participants’ learning process well and reached a significant better fit ($G^2$) for both age groups in comparison to a pure
chance baseline prediction. The baseline chance model predicted the choice of each of the three alternatives with a probability of 1/3 and had an average fit of $G^2 = -2 \sum \ln(p) = 466$ for the 7 blocks (210 trials). Figure 3 illustrates that the fit of the SSL theory is better than the baseline model for all participants.

**SSL parameters.** Figure 4a and 4b show the average parameter estimates and respective confidence intervals for the SSL model. The x-axis represents the average initial preference for TALLY ($\beta$), and the y-axis represents the strategy application error ($\varepsilon$). Non-overlapping error bars (representing 95% confidence intervals) can safely be interpreted as significant differences between mean parameter estimates (cf., Cumming & Finch, 2005). The diameter of each darker ring is proportional to the learning parameter ($w$), with larger rings representing more pronounced learning rates. The thinner surrounding rings denote the respective 95% confidence intervals.

We conducted separate analyses of variance with each parameter as the dependent variable and age group, environment, and their interaction as independent variables. Concerning the learning parameter, $w$, the findings suggest that older adults had more problems learning to select strategies compared to younger adults in the noncompensatory environment but learning rates were more similar between age groups in the compensatory environment. Our analysis identified a main effect of environment, $F(1, 96) = 10.93, p = .001, \eta^2_p = .10$, and an environment by age group interaction, $F(1, 96) = 7.90, p = .006, \eta^2_p = .08$, but no main effect of age group, $F(1, 96) = 0.51, p = .82, \eta^2_p < .01$. Follow-up analysis conducted separately for each environment, suggest that while there was a significant effect of age group in the noncompensatory environment, $F(1, 48) = 5.63, p = .02, \eta^2_p = .11$, the effect of age group in the compensatory environment was marginal, $F(1, 48) = 2.83, p = .10, \eta^2_p = .06$. When comparing learning in the two environment separately for each age group, we found that younger adults showed significantly different learning between the two environments, $F(1, 48) = 22.52, p < .001, \eta^2_p = .32$, while older adults did not, $F(1, 48) = 0.11, p = .75, \eta^2_p < .01$. These results likely represent a bottom effect by which age differences in learning do not emerge in the
compensatory environment in which little learning occurred. This may be partly attributed to participants' already high initial tendency to select compensatory strategies in this environment, which reduced the necessity to switch to a more successful strategy (Rieskamp & Otto, 2006).

Considering the initial preference for TALLY, $\beta_{\text{TALLY}}$, our results suggest that older adults preferred TALLY considerably more compared to younger adults, particularly in the compensatory environment. We identified a main effect of environment, $F(1, 96) = 13.89, p < .001, \eta_p^2 = .13$, and a main effect of age group, $F(1, 96) = 23.31, p < .001, \eta_p^2 = .20$, as well as an environment by age group interaction, $F(1, 96) = 10.58, p = .002, \eta_p^2 = .10$. We conducted follow-up analysis separately for each environment, and found there was a significant effect of age group in the compensatory environment, $F(1, 48) = 30.53, p < .001, \eta_p^2 = .39$, but not in the noncompensatory environment, $F(1, 48) = 1.33, p = .25, \eta_p^2 = .03$. When comparing initial strategy preferences as a function of environment separately for each age group, we found that younger adults showed similar preferences for TALLY in the two environments, $F(1, 48) = 0.14, p = .72, \eta_p^2 < .01$, while older adults differed in their preferences between the two environments, $F(1, 48) = 20.85, p < .001, \eta_p^2 = .30$.

Finally, regarding the strategy application error parameter, $\varepsilon$, older adults made significantly more application errors compared to younger adults, and made more errors in the compensatory environment compared to the noncompensatory one. We identified a main effect of environment, $F(1, 99) = 5.91, p = .02, \eta_p^2 = .06$, and a main effect of age group, $F(1, 96) = 28.11, p < .001, \eta_p^2 = .23$, but the environment by age group interaction was not significant, $F(1, 96) = 1.88, p = .17, \eta_p^2 = .02$. We conducted follow-up analyses separately for each environment, and found there was a significant effect of age group in both the noncompensatory, $F(1, 48) = 8.26, p = .006, \eta_p^2 = .15$, and compensatory environment, $F(1, 48) = 20.92, p < .001, \eta_p^2 = .30$. When comparing the two environments, we found that younger adults did not differ significantly in their strategy application error parameter between environments, $F(1, 48) = 1.58, p = .22, \eta_p^2 = .03$, while older adults had more application errors in the compensatory compared to the noncompensatory environment, $F(1, 48) = 4.40, p = .04, \eta_p^2 = .08$. In sum, older adults seem to have had more difficulties in correctly
applying strategies than younger adults and had more difficulties applying the compensatory WADD strategy compared to TTB.

In sum, we found significantly more learning, decreased preference for the compensatory strategy TALLY, and less application errors in the noncompensatory compared to the compensatory environment, which is compatible with the idea that many participants adapted their strategy use to the noncompensatory environment by relying on the simpler TTB. Concerning age, we found significant age-related differences in strategy selection. Older adults showed increased initial preference for the simple TALLY strategy and more difficulty learning compared to younger adults. In addition, older adults showed considerably more strategy application errors and had particularly difficulties in correctly applying strategies in the compensatory environment.

SSL parameters and performance. The SSL parameter estimates should be linked to performance and may help explain the reasons underlying differences in payoff between age groups. We first quantified the relative impact of the SSL parameters on the payoff differences separately for the two age groups in each environment by conducting regression analyses on payoff with the three SSL parameters as predictors. For younger adults, the models with SSL parameters as predictors explained 85% of the variance in payoff in the noncompensatory environment and 57% in the compensatory environment. Higher payoffs in the noncompensatory environment where associated with more pronounced learning, lower initial preference for a compensatory strategy, and fewer application errors ($B_w = -.62, p < .001; B_β = -.40, p < .001; B_ε = -.35, p = .001$; learning, initial preference for Tally, and strategy application error parameters, respectively). In the compensatory environment, only application errors were related to payoff ($B_w = -.15, p = .32; B_β = -.15, p = .31; B_ε = -.75, p < .001$). For older adults, the models with SSL parameters as predictors explained 87% of the variance in payoff in the noncompensatory environment and 81% in the compensatory environment. Individual differences in all SSL parameter estimates were significantly associated with older adults’ payoffs in both the noncompensatory environment, ($B_w = -.29, p < .01; B_β = -.35, p = .001; B_ε = -.87, p < .001$) and compensatory environment ($B_w = -.30, p < .01; B_β = -.27, p = .02; B_ε = -.82, p < .001$).
Second, we quantified the relative impact of the parameters on the payoff differences between age groups by conducting a hierarchical regression analysis on payoff with age as a predictor and, in a second step, with age and the three SSL parameters as predictors. As shown in Table 2, the SSL parameters captured the age differences in payoff quite well in both environments: While age was a significant predictor of performance when entered alone in the regression (Step 1), it showed a small, nonsignificant relation to payoff when the SSL parameters were considered (Step 2). Overall, the models including SSL parameters as predictors explained 88% of the variance in payoff in the noncompensatory environment and 82% in the compensatory environment. As can be seen in Table 2, the application error ($\varepsilon$) was the strongest predictor in both environments. These results support the idea that age-related differences in adaptive strategy selection stem to a large extent from problems in correctly executing decision strategies. Nevertheless, initial strategy preferences and learning abilities also contributed to performance and age differences thereof. Namely, poorer learning was associated with lower payoffs, while an increased preference for TALLY was disadvantageous, as is to be expected in environments favoring either TTB or WADD.

Our results suggest that strategy application errors represent a major constraint behind successful decision making, particularly in an environment in which cognitively demanding strategies need to be applied. Could these difficulties be associated with limited cognitive resources? In the noncompensatory environment, fluid ability measures (digit–symbol substitution, digit span) did not account for a significant portion of variance in strategy application errors, $R^2 = .06$, $F(3,46) = 1.00, p = .40$. In contrast, in the compensatory environment, individual differences in fluid abilities accounted for a large portion of the variance in strategy application errors, $R^2 = .32$, $F(3,46) = 7.30, p < .001$. This suggests that limitations in cognitive abilities, for example, due to aging, are an important factor in determining successful decision making when using complex decision strategies. Accordingly, age alone accounts for a considerable amount of variance in application errors in the compensatory environment, $R^2 = .30$, $F(1,48) = 20.53, p < .001$. Adding age to a model that includes fluid ability measures provides a relatively small increase in explained variance, $\Delta R^2 = .07$, $F(1,45) =$
4.93, \( p = .03 \), suggesting that fluid abilities account for 77% of age-related variance in application errors \((.30 - .07 = .23)\). Note that all results obtained using hierarchical regression with an extreme group design must be interpreted with caution as these analyses are susceptible to spurious associations occurring between the mediator and the dependent variable (e.g., Lindenberger & Potter, 1998; Hofer & Sliwinski, 2002).

In sum, the SSL theory (Rieskamp & Otto, 2006) allowed us to distinguish between different processes underlying younger and older adults’ decisions, namely, initial preference for strategies, learning rate, and strategy application errors. We were thus able to evaluate the contribution of each of these components to age differences in performance. Our results suggest that strategy application errors may have played a major role in explaining age differences in performance, particularly in the compensatory environment, in which many older adults relied on TALLY, a less demanding compensatory strategy that, in contrast to WADD, does not require differentiated weighting of cues according to their validity. Consequently, one reason for older adults’ increased reliance on TALLY may have been the lack of the cognitive resources necessary to apply the more cognitively demanding WADD.

**Discussion**

We examined younger and older adults’ strategy selection learning as a function of performance feedback in an inference task. Each participant made inferences in either a condition in which the payoff structure favored the use of the simple strategy, TTB, or a condition that favored the use of the information-intensive WADD strategy. Compared to younger adults, older adults showed poorer decision performance. However, older adults did significantly better in the noncompensatory environment, which favored the simple TTB, compared to the compensatory environment that favored the use of the more complex, information-intensive WADD strategy. Also, in an environment favoring the compensatory WADD, older adults’ often ignored cue validity information and relied on a simpler compensatory strategy that ignores cue weights, TALLY. Overall, this suggests that older adults can learn to select a cognitively simple strategy such as TTB
when appropriate, while they have more difficulties selecting the more demanding WADD strategy, and may default to using simpler compensatory strategies such as TALLY.

We relied on a computational model to account for participants’ strategy selection learning (SSL; Rieskamp & Otto, 2006). Our modeling investigated whether age differences in decision making performance were related to three factors, (1) the initial preference for decision strategies, (2) errors made when applying a strategy and (3) general learning deficits. Individual differences differences in application errors largely explained older adults’ worse performance compared to younger adults’, suggesting that age differences in performance may to a large extent stem from an increase in strategy application errors with age. Also, strategy application errors were related to fluid abilities in the compensatory environment, suggesting that cognitive resources can determine successful strategy application in cognitively demanding environments. The amount of strategy application errors depended on the structure of the environment with older adults making more errors in the compensatory compared to the noncompensatory environment. Thus, although older adults performed worse than younger adults in the noncompensatory environment, it seems that decision environments that favor simple strategies can help improve decision-making performance in old age, and older adults can benefit from strategies with reduced cognitive load (Hanoch et al., 2007; Mata et al., 2007). In addition to age differences in application errors and initial strategy preferences, we found support for the idea that older adults have difficulties in learning from experience. Resonating with research showing age difference in the ability to learn the value of options (e.g. Wood, et al., 2005), we found that in the noncompensatory environment older adults learning rate was lower than the learning rate of younger adults. Our modeling results did not find a similar age difference in the compensatory environment, however, this probably was due to a bottom effect as both younger and older adults, showed little learning in this condition.

Implications

Our findings match previous work showing that younger and older adults may differ in their initial preferences for simpler strategies (Lemaire et al., 2004; Mata et al., 2007). In addition, our
results match previous findings on the impact of aging in learning from experience that point to age-related deficits in learning the value of cues (e.g., Chasseigne et al., 2004) and options from performance feedback (e.g., Wood et al., 2005; Denburg et al., 2006). However, we go further in showing that older adults may also have difficulties learning the value of decision strategies.

There is considerable evidence that older adults have difficulties in executive function tasks involving learning the applicability of simple rules, such as the Wisconsin Card Sort (Rhodes, 2004) or the Tower of London (Andrés & Van der Linden, 2000; Phillips, Gilhooly, Logie, Della Sala, & Wynn, 2003). Our work extends this line of research by suggesting that learning effects in rule/strategy learning differ as a function of environment structure, which can favor strategies demanding different degrees of cognitive effort. Also, we provide a computational account of strategy selection learning which suggests that age differences in performance in decision making may be largely attributable to individual differences in strategy application errors.

**Age Differences in Attention to Gains vs. Losses**

The role of motivational changes in age differences in decision making from experience is not yet clear. Wood et al. (2005) identified a positive bias in learning, whereby older adults paid more attention to gain vs. loss outcomes in a probabilities learning task. Samanez-Larkin et al. (2007) found decreased attention to losses by older adults in anticipation of monetary outcomes in a financial game. However, Samanez-Larkin et al. found no evidence for age differences in response to negative versus positives outcomes. In contrast, Frank and Kong (2008) identified a negative learning bias in a probabilistic selection task, for older-old adults (but not younger-old), whereby they tended to learn more from negative compared to positive consequences of their decisions.

We also used SSL to examine the role of age differences in attention to gains versus losses in strategy selection. For this purpose, we tested a version of SSL in which an additional parameter representing the attention to positive feedback (relative to negative) was allowed to vary freely for each participant (see Equation 6 in the Appendix). We compared the alternative and original model by using the Akaike Information Criterion (AIC; Akaike, 1974), which considers both the fit and
complexity of a model (i.e., the number of free parameters). The model with the additional parameter did not explain the data better than the simpler SSL model and was the preferred model for only a minority of both younger (4%) and older (2%) participants. Overall, these results suggest that the simpler SSL model reported in our paper provides a parsimonious account of the data and that age-related differences in dealing with positive versus negative feedback did not have an impact on strategy selection learning in our task. There are of course a number of differences between our task and the ones used in previous work. For example, probability learning tasks in which participants have to learn about the values of objects (Frank & Kong, 2008; Samanez-Larkin et al., 2007; Wood et al., 2005) are likely to involve implicit learning, which depends heavily on the basal ganglia. In turn our probabilistic inference task may tap more into explicit learning systems involving prefrontal areas. One potential avenue for future research would be to investigate the overlap between brain structures underlying performance in both types of tasks and how age differences in these may lead to biases in attention to gains or losses.

**Computational Modeling**

We adopted a computational modeling approach to gain some insight into how aging may affect decision making. Computational models have advantages over verbal theories because their parameters can summarize individual differences in meaningful components for which the interrelations are well specified. The SSL theory (Rieskamp & Otto, 2006) in particular allowed us to go a step beyond participants’ overt behavior and identify possible mechanisms underlying age differences in strategy use. Specifically, the SSL model allowed us to separate initial strategy preferences, learning abilities, and application errors so we could assess their contributions to performance (payoff) using standard multiple regression analysis. A comprehensive formal model also offers the technical advantage of accounting for several aspects of behavior simultaneously. For example, it is not clear how to quantify strategy errors without assuming which strategy had been selected. SSL deals with this issue by quantifying strategy application errors given assumptions about the strategy selected on each trial. By considering different components simultaneously, we
were able to show that application errors have more pronounced effects when people learn to select a complex compensatory strategy and are of less importance when selecting a simple noncompensatory strategy. Finally, numeric parameter estimates can be used to provide quantitative predictions about behavior in circumstances others than those already observed. The goal of our study was to provide a description of younger and older adults strategy selection learning but future studies could rely on similar paradigms and models to make predictions about age differences, for example, in dynamic environments in which the relation between cues and criterion changes over time (see Rieskamp, 2006, 2008, for such studies with younger adults).

Conclusion

Older adults’ ability to rely on strategies successfully may be compromised when having to learn the strategy–environment match from performance feedback. Our findings nevertheless support the idea that old adults can improve their strategy use and overall performance with training (cf., Brehmer, Li, Müller, von Oertzen, & Lindenberger, 2007), at least in some circumstances. In particular, the results suggest that the structure of the environment and the complexity of the strategy that it favors may play an important role in fostering learning. Specifically, both younger and older adults were better able to make decisions in an environment favoring the use of a simple noncompensatory decision strategy compared to a more demanding environment. Consequently, our work contributes to understanding the limits of adaptivity, thus shedding light on the ability of the aging decision maker to learn from past successes and failures.
Acknowledgments

This work was supported by a postdoctoral grant from the Portuguese Foundation for Science and Technology to the first author and a research grant by the German research foundation to the second and third authors (RI 1226/5). We thank Gregor Caregnato for assistance in conducting the experiment.
Footnotes

1. The initial preference for the other two strategies (TTB and WADD) was set as \((1 - \beta_{\text{TALLY}})/2\) implying equal preference for TTB and WADD. Alternatively, we could have given two of the three strategies their own initial preference parameters as suggested by Rieskamp and Otto (2006). We implemented such a version of the SSL theory but the increased complexity of the model (one additional free parameter) could not be justified by an only moderate increase of goodness-of-fit. We therefore report only the more parsimonious model with one single initial preference parameter.
References


Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded


Appendix

Computational Specification of the Strategy Selection Learning 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 that expectancies are updated on the basis of feedback. We assume that the strategy repertoire can be reduced to three strategies: TTB, TALLY, and 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

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

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

$$q_1(i) = r_{\text{max}} \cdot w \cdot \beta_i$$  \hspace{1cm} (2)

where $r_{\text{max}}$ is the maximum payoff that can be obtained by a correct decision, $w$ is the initial association parameter (constrained by $w > 0$), and $\beta$ 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 $\beta$ for WADD and TTB (i.e., $\beta_{\text{WADD}} = \beta_{\text{TTB}}$), so that a value of $\beta_{\text{TALLY}} = 0.40$ implies a value for $\beta_{\text{WADD}} = \beta_{\text{TTB}} = 0.30$. Consequently, $\beta > 1/3$ implies that the decision maker will select TALLY with a larger probability at the beginning of the task than TTB or WADD. We also tested a version of SSL in which $\beta_{\text{TALLY}}$ and $\beta_{\text{WADD}}$ were both optimized (given one additional free parameter). However, this more complex version of SSL did not improve the fit of the model substantially, so that we kept the more parsimonious version.

After a decision is made, the expectancies of the cognitive strategies are updated for the next trial $t$ by
\[ q_i(t) = q_{i-1}(t) + I_{i-1}(t) \cdot r_{i-1}(t) \] (3)

where \( r_{i-1}(t) \) is the reinforcement defined by the produced payoff of a strategy and \( I_{i-1}(t) \) is an indicator function that denotes whether a strategy has been selected. The indicator function \( I_{i-1}(t) \) 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, 1) the necessary information for applying the strategy was acquired, and 2) 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 \( k \) as the number of available alternatives). The conditional probability of choosing alternative \( a \) given application error \( \varepsilon \) is

\[ p_i(a \mid i, \varepsilon) = (1 - \varepsilon) \cdot p_i(a \mid i) + \frac{\varepsilon}{k-1} \cdot p_i(\bar{a} \mid i) \] (4)

where \( p_i(\bar{a} \mid i) \) 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.

\[ p_i(a) = \sum_{i=1}^{N} p_i(i) \cdot p_i(a \mid i, \varepsilon) \] (5)

In sum, Equations 1–5 provide a computational description of the processes involved in learning to adaptively select strategies. SSL’s predictions depend on its three parameters: the initial association parameter \( w \), the initial preference parameter \( \beta \), and the application error parameter \( \varepsilon \).

Specifically, SSL predicts the probability with which a participant will choose each of the available alternatives conditioned on past choices and the received feedback.

We also tested an additional version of SSL that considers the potentially differential impact of
positive and negative performance feedback. In this version, the reinforcement used to update strategy expectancies in Equation 3 was defined as

\[ r_{i-1}(i) = L(r) \cdot r_{i-1}(i) \]  

(6)

where \( L(r) \) represents an indicator function that takes the value 1 when \( r > 0 \) and \( g \) (with \( g > 1 \)) otherwise. This alternative version, which incorporates different attention of decision makers to losses versus gains includes one additional free parameter.
Table 1: Means (SD) for Total Payoff and Search Variables by Age Group and Environment

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<tr>
<th></th>
<th>Younger adults</th>
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<th>Older adults</th>
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<td>Compensatory</td>
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<td>11.0 (3.0)</td>
<td>9.5 (2.4)</td>
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<td>.80 (.25)</td>
<td>.87 (.19)</td>
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<td>VALIDITY</td>
<td>.66 (.36)</td>
<td>.48 (.41)</td>
<td>.23 (.32)</td>
<td>.12 (.26)</td>
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Table 2: Summary of Hierarchical Regression Analysis with Payoff as the Dependent Variable and Age and SSL Parameters as Independent Variables

<table>
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<td>Application Error (ε)</td>
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Figure Captions

Figure 1.

Information board employed in the experiment.

Figure 2.

Payoff in each block for younger adults (circles) and older adults (squares) and strategy classification for the two age groups. $Y =$ Younger adults, $O =$ Older adults, TTB = take-the-best, WADD = weighted-additive rule.

Figure 3.

Strategy selection learning theory’s (SSL’s) fit for each individual participant in comparison to a pure chance prediction. Each bar represents the fit of the SSL to each participant in the younger or older age group. The baseline chance model represented with the horizontal line predicted the choice of each of the three alternatives with a probability of $1/3$ and had an average fit of $G^2 = -2 \sum \ln(p) = 466$ for the 7 blocks (210 trials).

Figure 4.

Participants’ parameter values in the noncompensatory (A) and compensatory environments (B). The $x$-axis represents the average initial preference for TALLY ($\beta$), and the $y$-axis represents the strategy application error ($\varepsilon$), with horizontal and vertical error bars representing 95% confidence intervals. The diameter of the darker ring is proportional to the learning parameter ($w$), with larger circles representing more learning, and the thinner surrounding rings denoting the respective 95% confidence intervals.
Figure 1

Which will you buy? A B C

Trial: 1
Figure 2

Noncompensatory Environment

Compensatory Environment
Figure 3

[Graph showing model fit (G^2) for older and younger groups, with baseline G^2 indicated.]
Figure 4

Noncompensatory

Compensatory

Application Error

Preference Tally

Older

Younger

Older

Younger