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Learning to Choose: Cognitive Aging and Strategy Selection Learning in Decision Making

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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? We examined younger and older adults' strategy selection learning in a probabilistic inference task using a computational model of strategy selection learning. Older adults showed poorer decision performance compared with 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, adaptivity

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 (Gigerenzer, Todd, & the ABC Research Group, 1999; Payne, Bettman, & Johnson, 1993) literatures. 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 past performance, the stocks' cost, and so forth. One type of strategy that can be used to choose between stocks is a compensatory strategy, such as a weighted-additive (WADD) rule (e.g., Payne et al., 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 tradeoffs between positive and negative information. The WADD rule 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 take-the-best (TTB; Gigerenzer & Goldstein, 1996), which focuses on the single most important cue (e.g., 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 depends 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 valid information, a compensatory strategy performs 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.

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Findings from research on arithmetic skill suggest 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 with younger adults, because of age-related cognitive decline (Mata, Schooler, & Rieskamp, 2007; Pachur, Mata, & Schooler, 2009). For example, Mata et al. (2007) 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, rather 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 may 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 et al. (2005) asked younger and older adults to play a version of the Iowa Gambling Task (Bechara, Damasio, Damasio, & Anderson, 1994), in which people learn on the basis of outcome feedback which of several options produces on average the largest payoff, and they found no age differences in terms of overall performance scores (for a similar result, see Kovalchik, Camerer, Grether, Plott, & Allman, 2005). However, computational modeling of participants' decision making suggested that older adults had more trouble learning the value of options because of more rapid forgetting as well as motivational changes in increased attention to monetary gains as opposed to losses compared with younger adults. In sum, in addition to differences in initial strategy preferences (Mata et al., 2007; Pachur et al., 2009), 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 strategy, in comparison with 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 on the basis of 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 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% women) and 50 older adults (mean age = 69.0 years, *SD* = 3.6, range = 60–79; 58% women) 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 they earned 0.10 euros for each correct decision and paid 0.05 euros for each incorrect decision.

Design

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

Materials

We designed an environment in which the WADD strategy performed best (compensatory environment) and one in which the TTB strategy performed best (noncompensatory 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, 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 was constituted by three options that varied on six 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 one 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. For the noncompensatory environment, the average cue validities were the following: 82%, 67%, 58%, 50%, 42%, and 36%. For the compensatory environment, the average cue validities were the following: 72%, 65%, 58%, 50%, 43%, and 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; and comparison with an index with average ratings of 3.9, 3.4, 3.4, 3.1, 2.6, and 2.2 on a scale ranging from −7 to 7, respectively) and a less dispersed compensatory set (expert ratings; cost/gain ratio; international company; political stability; revenue; stock ratings; and comparison with an index 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 it could 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 stock's 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 searching and in which order to click on cues (see Figure 1). The cue validities were visible throughout the task

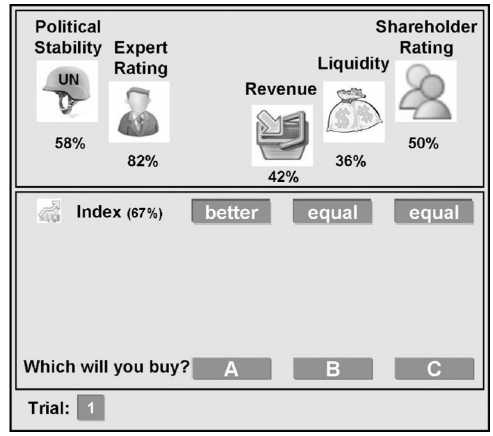

Figure 1. Information board used in the experiment.

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 on. 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–symbol substitution and digit span tasks.

Results

In the following, we first report participants' overall performance by examining their payoffs. We then present participants' predecisional information search and describe the strategies that 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 on average poorer performance compared with 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 they benefitted considerably 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 with age group, environment, and their interaction as the 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 × 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 environment compared with the compensa-

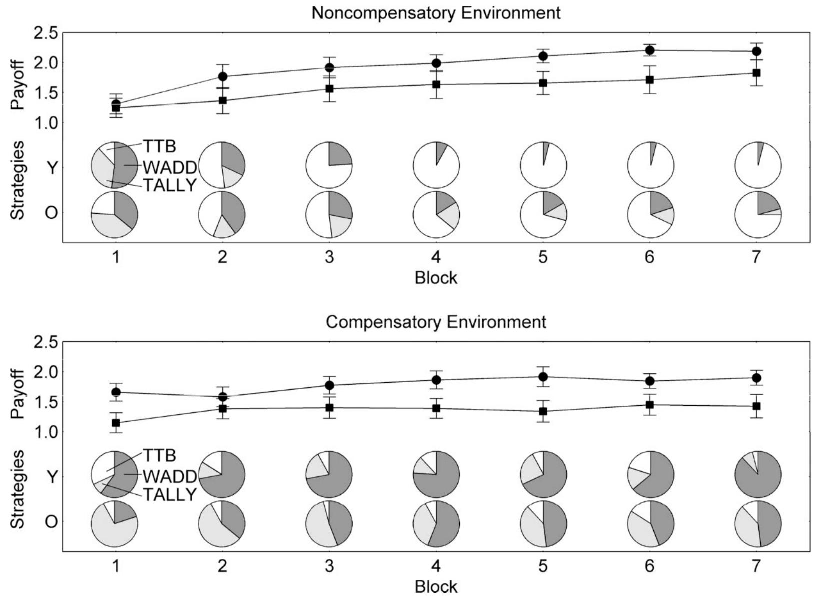

Figure 2. Payoff in each block for younger adults (circles) and older adults (squares) and strategy classification for the two age groups. Y = younger adults; O = older adults; TTB = take-the-best strategy; WADD = weighted-additive strategy; TALLY = assigning equal weights to cues and adding them to reach a decision. Error bars represent 95% confidence intervals.

tory environment, as we found a Block × Environment interaction, $F(6, 91) = 4.03$, $p < .001$, $\eta_p^2 = .21$. Concerning age differences in learning, no Block × Age Group interaction emerged, $F(6, 91) = 1.28$, $p = .27$, $\eta_p^2 = .08$. However, there was a significant Block × Environment × 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 × Age Group interaction in the noncompensatory environment, $F(6, 43) = 1.91$, $p = .10$, $\eta_p^2 = .21$, but we identified a significant Block × Age Group interaction in the compensatory environment, $F(6, 43) = 2.53$, $p = .04$, $\eta_p^2 = .26$, which suggests that payoff increased similarly for younger and older adults in the noncompensatory environment but not in the compensatory environment. We further conducted equivalent analyses separately for each environment and age group and found effects of trial block in the noncompensatory environment for both the younger age group, $F(6, 19) = 17.51$, $p < .001$, $\eta_p^2 = .85$, and the older age group, $F(6, 19) = 7.39$, $p < .001$, $\eta_p^2 = .70$. In the compensatory environment, however, we found a significant effect of trial block for the younger age group, $F(6, 19) = 2.98$, $p = .03$, $\eta_p^2 = .49$, but not the older age group, $F(6, 19) = 1.77$, $p = .16$, $\eta_p^2 = .36$. In sum, our analyses suggest that although older adults improved their performance on the basis of feedback in the noncompensatory environment similarly to younger adults, older adults may have benefited less from feedback in the environment favoring the more complex WADD strategy.

Information Search

We used two measures to describe each participant's information search. First, we calculated the mean proportion of information searched per trial (PROP) by computing the proportion of cue values viewed in each trial relative to all available cue values (3 options × 6 cues = 18 cue values). Second, we computed a measure of information searched in the order of validity (VALIDITY) by calculating the proportion of trials in which the participant clicked on cues according to the cue-validity ordering relative to the total number of trials. The averages for the different groups across the experiment are summarized in Table 1. Overall, our results suggest that although there were no significant age differences in the total amount of information searched, younger adults tended to search more often according to the supplied cue-validity orderings compared with older adults.

We conducted separate repeated measures analysis of variance for each search variable using the search in each block as dependent variables and age group and environment as independent variables. The results concerning 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, $F(1, 96) = 2.80$, $p = .10$, $\eta_p^2 = .03$, suggesting that participants searched for more information in the compensatory environment; however, there was no effect of age group, $F(1, 96) = 0.09$, $p = .77$, $\eta_p^2 < .01$, and no Age Group × Environment interaction, $F(1, 96) = 0.01$, $p = .94$, $\eta_p^2 < .01$. We also found no effect of block, $F(6, 91) = 1.36$, $p = .24$, $\eta_p^2 = .08$; no Block × Age Group interaction, $F(6, 91) = 0.43$, $p = .86$, $\eta_p^2 = .03$; no Block × Environment interaction, $F(6, 91) = 1.63$, $p = .15$, $\eta_p^2 = .10$; or no Block × Environment × Age Group interaction, $F(6, 91) = 1.70$, $p = .13$, $\eta_p^2 = .10$.

The results concerning VALIDITY suggest that younger adults searched more often in order of validity, particularly in the noncompensatory environment. We identified a significant effect of environment, $F(1, 96) = 4.41$, $p = .04$, $\eta_p^2 = .04$, and an effect of

Table 1
Means (and Standard Deviations) for the Total Payoff and Search Variables by Age Group and Environment

	Younger adults		Older adults	
	Noncompensatory	Compensatory	Noncompensatory	Compensatory
Variable	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)
Payoff	13.5 (2.0)	12.5 (1.6)	11.0 (3.0)	9.5 (2.4)
PROP	0.79 (0.20)	0.85 (0.14)	0.80 (0.25)	0.87 (0.19)
VALIDITY	0.66 (0.36)	0.48 (0.41)	0.23 (0.32)	0.12 (0.26)

Note. PROP = the mean proportion of information searched per trial; VALIDITY = information searched in the order of validity.

age group, $F(1, 96) = 32.86$, $p < .001$, $\eta_p^2 = .26$, but no Age Group × Environment interaction, $F(1, 96) = 0.31$, $p = .58$, $\eta_p^2 < .01$. The analysis revealed an effect of block, $F(6, 91) = 7.26$, $p < .001$, $\eta_p^2 = .32$, and a Block × Age Group interaction, $F(6, 91) = 2.22$, $p = .05$, $\eta_p^2 = .13$, but no Block × Environment interaction, $F(6, 91) = 1.61$, $p = .15$, $\eta_p^2 = .10$, or no Block × Environment × Age Group interaction, $F(6, 91) = 1.02$, $p = .42$, $\eta_p^2 = .06$. Follow-up analyses conducted separately for the two age groups suggest that younger adults significantly searched more often for the cues in the order of their validities from the first block ($M = 0.34$, $SD = 0.35$) to the last block ($M = 0.66$, $SD = 0.44$), $F(6, 43) = 6.63$, $p < .001$, $\eta_p^2 = .48$, whereas older adults did not ($M = 0.10$, $SD = 0.20$ vs. $M = 0.23$, $SD = 0.38$), $F(6, 43) = 1.40$, $p = .24$, $\eta_p^2 = .16$. In sum, although there were no significant changes across blocks in the total amount of information searched or the age differences thereof, younger adults increased their tendency across blocks to search according to the cue validities, whereas 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 $G^2 = -2\Sigma \ln(p)$, where p is the probability with which the model predicts the participant's choices. 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 guessed on all 210 trials, corresponding to a 1/3 probability to choose an option on any given trial, G^2 would be roughly 466. 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 (a) initial strategy preferences in the absence of feedback and (b) 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, $\chi^2(2, N = 100) = 0.17$, $p = .92$, $w_{Effect\ Size}$ (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, 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 with 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: Although the majority of older adults (76%) were classified as selecting the appropriate TTB strategy in the noncompensatory environment, only about half (48%) were classified as selecting WADD in the compensatory environment, $\chi^2(1, N = 50) = 16.64$, $p < .001$, $w_{ES} = .28$.

Although information search and integration are theoretically independent, there are likely empirical relations between the two. In particular, TTB users may tend to be more frugal in their information search and follow cue-validity ordering more often compared with TALLY and WADD users. Indeed, across experimental conditions, those participants who were classified as using the noncompensatory TTB strategy searched, on average, less information ($M = 0.74$, $SD = 0.25$) compared with those relying on the compensatory strategies, TALLY ($M = 0.88$, $SD = .014$) and WADD ($M = 0.89$, $SD = 0.23$), $F(2, 94) = 6.20$, $p = .003$, $\eta_p^2 = .12$. Concerning proportion validity search, TTB users searched more often according to VALIDITY ($M = 0.58$, $SD =$

0.44), followed by WADD users (M = 0.38, SD = 0.47) and TALLY users (M = 0.18, SD = 0.37), $F(2, 94) = 3.13$, $p = .05$, $\eta_p^2 = .06$. We found no significant Strategy Classification × Age Group interaction, suggesting that the relation between strategy use and information search was similar for the two age groups. Overall, these findings suggest that the classification procedure was able to capture meaningful patterns in both younger and older adults' choices.

Strategy Selection Learning (SSL)

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 SSL theory (Rieskamp & Otto, 2006) to model each participant's learning process. Then, by considering age differences in model parameter estimates corresponding to each decision component, we hoped to explain why older adults performed worse and were less adaptive in selecting decision strategies as a function of the environment compared with 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 strategy's prediction, which is regarded as a strategy application error.

Model fitting. The calculations corresponding to each of the steps underlying SSL according to the SSL theory are formalized in the Appendix (also see Rieskamp, 2006, 2008; Rieskamp & Otto, 2006). 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' SSL into three components (parameters). First, the initial strategy preference parameter, β_{TALLY}, represents the initial preference for the TALLY strategy relative to other strategies in the repertoire. We used TALLY as the baseline strategy because this was the most prevalent strategy in the first block of trials according to our strategy classification analysis. The initial preference parameter is constrained such that $\beta_{TALLY} + \beta_{WADD} + \beta_{TTB} = 1$, and we assumed an equal initial preference parameter β_i for WADD and TTB ($\beta_{WADD} = \beta_{TTB}$). Consequently, a value of $\beta_{TALLY} = 0.40$ implies a preference for the TALLY strategy relative to the other strategies in the repertoire ($\beta_{WADD} = \beta_{TTB} = 0.30$).[1] Second, an initial association parameter, w, represents the ability to overcome initial preferences, that is, a learning rate, with smaller values representing faster learning. Finally, an error parameter, ε, represents 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 the Appendix). Overall, SSL captured participants' learning processes well and reached a significant better fit (G^2) for both age groups in comparison with 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 seven blocks (210 trials). Figure 3 illustrates that the fit of the SSL theory is better than the baseline model for all participants.[2]

SSL parameters. Table 2 presents the average SSL parameter estimates for the two age groups in each environment. Note that higher values of the learning parameter, w, represent slower learning rates as they imply more feedback trials are necessary to overcome the initial strategy expectancies (see the Appendix for a numerical example). We conducted separate analyses of variance with each parameter as the dependent variable and with age group, environment, and their interaction as the independent variables. Concerning the learning parameter, w, the findings suggest that, overall, participants learned faster in the noncompensatory environment. Further, older adults had more problems learning to select strategies compared with younger adults in the noncompensatory environment, but learning rates were more similar between age groups in the compensatory environment. Note that age group differences in the learning parameter were in opposite directions in the two environments, which is likely a reflection of most younger adults not learning much in the compensatory environment, as the majority preferred WADD from the outset (see Figure 2). The heterogeneity in younger adults' initial strategy preferences in the compensatory environment likely led to the increased variability in younger adults' learning estimates in this environment. In this vein, our analysis identified a main effect of environment, $F(1, 96) = 10.93$, $p = .001$, $\eta_p^2 = .10$, and an Environment × Age Group interaction, $F(1, 96) = 7.90$, $p = .006$, $\eta_p^2 = .08$, but no main effect of age group, $F(1, 96) = 0.51$, $p = .82$, $\eta_p^2 < .01$. Follow-up analysis conducted separately for each environment suggests that although there was a significant effect of age group in the noncompensatory environment, $F(1, 48) = 5.63$, $p = .02$, $\eta_p^2 = .11$, the effect of age group in the compensatory environment was marginal, $F(1, 48) = 2.83$, $p = .10$, $\eta_p^2 = .06$. When comparing learning in the two environments separately for each age

[1] The initial preference for the other two strategies (TTB and WADD) was set as $(1 - \beta_{TALLY})/2$, 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.

[2] Some work suggests that age-related differences in attention to gains and losses may have significant impact on decision making from experience (Frank & Kong, 2008; Samanez-Larkin et al., 2007; Wood et al., 2005). Consequently, we also used SSL to explore the role of age differences in attention to gains versus losses in SSL. In particular, 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. The model with the additional parameter was the preferred model for only a minority of both younger and older participants. These results suggest that individual differences in attending to positive versus negative feedback did not have an impact on SSL in our task.

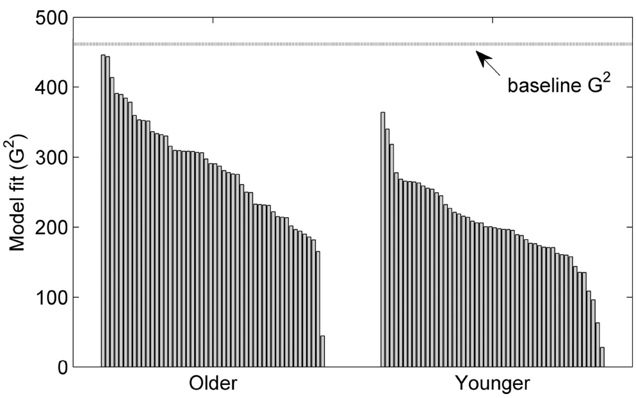

Figure 3. Strategy selection learning (SSL) theory's fit for each individual participant in comparison with a pure chance prediction. Each bar represents the SSL theory's fit to each participant in the younger or older age group. The baseline chance model represented with the horizontal line predicted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

group, we found that younger adults showed significantly different learning between the two environments, $F(1, 48) = 22.52$, $p < .001$, $\eta_p^2 = .32$, whereas older adults did not, $F(1, 48) = 0.11$, $p = .75$, $\eta_p^2 < .01$. These results likely represent a floor effect by which age differences in learning do not emerge in the compensatory environment in which little learning occurs. This may be partly attributed to participants' already high initial tendency to select compensatory strategies in this environment, which reduces the necessity to switch to a more successful strategy (Rieskamp & Otto, 2006).

Considering the initial preference for TALLY, β_{TALLY}, our results suggest that older adults preferred TALLY considerably more compared with younger adults, particularly in the compensatory environment. As can be seen in Table 2, the older adults in the compensatory environment showed a strong preference for TALLY ($\beta_{\text{TALLY}} = .69$), whereas in the noncompensatory environment and for younger adults in both environments, the initial preference parameter value was closer to .33, thus indicating a more equal preference distribution for the three strategies. Accordingly, 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 × Age Group interaction, $F(1, 96) = 10.58$, $p = .002$, $\eta_p^2 = .10$. We conducted a follow-up analysis separately for each environment and found that 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, $F(1, 48) = 0.14$, $p = .72$, $\eta_p^2 < .01$, whereas 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, ε, older adults made significantly more application errors compared with younger adults, and they made more errors in the compensatory environment compared with the noncompensatory environment. 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 × 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 that there was a significant effect of age group in both the noncompensatory environment, $F(1, 48) = 8.26$, $p = .006$, $\eta_p^2 = .15$, and the 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, $F(1, 48) = 1.58$, $p = .22$, $\eta_p^2 = .03$, whereas older adults had more application errors in the compensatory environment compared with 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 with TTB.

In sum, we found significantly more learning, decreased preference for the compensatory strategy TALLY, and less application errors in the noncompensatory environment compared with 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 strategy. Concerning age, we found significant age-related differences in strategy selection. Older adults showed increased initial preference for the simple TALLY strategy and had more difficulty in learning compared with younger adults, at least in the noncompensatory environment. In addition, older adults showed considerably more strategy application errors and had difficulties particularly in correctly applying strategies in the compensatory environment.

Table 2
Means (and Standard Deviations) for Strategy Selection Learning Parameter Estimates by Age Group and Environment

	Younger adults		Older adults	
	Noncompensatory	Compensatory	Noncompensatory	Compensatory
Parameter	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)
Learning (w)	26.9 (27.6)	74.2 (41.4)	50.4 (41.0)	54.2 (42.5)
Initial preference (β)	0.28 (0.19)	0.31 (0.24)	0.36 (0.26)	0.69 (0.25)
Application error (ε)	0.04 (0.04)	0.06 (0.06)	0.11 (0.11)	0.17 (0.11)

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 different SSL parameters on payoff separately for the two age groups in each environment. For this purpose, we conducted regression analyses with the total payoff in the decision task as a criterion and 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 were associated with more pronounced learning, lower initial preference for a compensatory strategy, and fewer application errors ($B_w = -0.62$, $p < .001$; $B_\beta = -0.40$, $p < .001$; $B_\varepsilon = -0.35$, $p = .001$; learning, initial preference for TALLY, and strategy application error parameters, respectively). In the compensatory environment, only application errors were related to payoff ($B_w = -0.15$, $p = .32$; $B_\beta = -0.15$, $p = .31$; $B_\varepsilon = -0.75$, $p < .001$). 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 ($B_w = -0.29$, $p < .01$; $B_\beta = -0.35$, $p = .001$; $B_\varepsilon = -0.87$, $p < .001$) and the compensatory environment ($B_w = -0.30$, $p < .01$; $B_\beta = -0.27$, $p = .02$; $B_\varepsilon = -0.82$, $p < .001$).

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 can be seen in Table 3, the SSL parameters captured the age differences in payoff quite well in both environments: Although 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 3, the application error (ε) 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, whereas an increased preference for TALLY was disadvantageous, as is to be expected in environments favoring either TTB or WADD. 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., Hofer & Sliwinski, 2001; Lindenberger & Potter, 1998).

Table 3
Summary of Hierarchical Regression Analysis With Payoff as the Dependent Variable and With Age and Strategy Selection Learning Parameters as the Independent Variables

Variable	*B*	*t*	*p*
Noncompensatory environment ($N = 50$)			
Step 1			
Age	−0.45	3.46	.001
Step 2			
Age	0.01	0.78	.13
Learning (*w*)	−0.38	5.92	<.001
Initial preference (β)	−0.30	4.96	<.001
Application error (ε)	−0.73	13.34	<.001
Compensatory environment ($N = 50$)			
Step 1			
Age	−0.58	4.94	<.001
Step 2			
Age	0.07	0.80	.43
Learning (*w*)	−0.19	2.74	.01
Initial preference (β)	−0.21	2.49	.02
Application error (ε)	−0.79	9.72	<.001

The results above 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? For younger adults, measures of fluid ability (digit–symbol substitution, digit span) were not correlated with strategy application errors regardless of environment (all *r*s < .22). For older adults, individual differences in digit span were also not related to application errors in either environment (both *r*s < .09). However, older adults' individual differences in processing speed were correlated with strategy application errors in the noncompensatory ($r = -.36$, $p = .08$) and the compensatory ($r = -.45$, $p = .02$) environments. Overall, these results support the idea that older adults' cognitive limitations are an important factor behind errors in applying complex decision strategies.

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 the compensatory environment, 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' SSL 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 with younger adults, older adults showed poorer decision performance. However, older adults did significantly better in the noncompensatory environment, which favored the simple TTB, compared with the compensatory environment that favored the use of the more complex, information-intensive WADD strategy. Also, in an environment favoring the compensatory WADD strategy, older adults often ignored cue-validity information and relied on a simpler compensatory strategy, TALLY, that ignores cue weights. Overall, this suggests that older adults can learn to select a cognitively simple strategy, such as TTB, when appropriate, although 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' SSL (Rieskamp & Otto, 2006). Our modeling investigated whether age differences in decision-making performance were related to three factors: (a) the initial preference for decision strategies, (b) errors made when applying a strategy, and (c) learning abilities. The results suggest that older adults preferred simpler strategies compared with younger adults, particularly in the compensatory environment in which they often relied on the simpler TALLY strategy. Older adults made significantly more errors in applying strategies, and individual differences in application errors largely explained older adults' worse performance compared with younger adults' performance, 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 significantly 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 environment compared with 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, Wood, & Rice, 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 may have had more problems overcoming their initial strategy preferences, as reflected by higher estimates of the w parameter relative to younger adults. Our modeling results did not find a similar age difference in the compensatory environment, possibly because of a floor 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., Denburg et al., 2006; Wood et al., 2005). 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 SSL that suggests that age differences in performance in decision making may be largely attributable to individual differences in strategy application errors.

Computational Modeling

We adopted a computational modeling approach to gain 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) 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 that we could assess their contributions to performance. A comprehensive formal model 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 that interact with each other, 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. Consequently, the computational modeling results led us to conclude that the learning rate between younger and older adults were different in the noncompensatory environment, whereas they were equivalent in the compensatory environment. Thus, our model suggests that differences in payoff are mostly due to older adults' application errors in the compensatory environment—a conclusion that could not have been drawn by examining the payoff data alone. 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' SSL, 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 (for such studies with younger adults, see Rieskamp, 2006, 2008).

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 older 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 with 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.

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Appendix

Computational Specification of the Strategy Selection Learning (SSL) Theory

The SSL theory (Rieskamp & Otto, 2006) assumes (a) that a person has subjective expectancies associated with each decision strategy, (b) that a person selects strategies proportional to his or her expectancies, and (c) that expectancies are updated on the basis of feedback. We assume that the strategy repertoire can be reduced to three strategies: take-the-best (TTB), assigning equal weights to cues and adding them to reach a decision (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 WADD and TTB (i.e., $\beta_{\mathrm{WADD}} = \beta_{\mathrm{TTB}}$), so that a value of $\beta_{\mathrm{TALLY}} = 0.40$ implies a value for $\beta_{\mathrm{WADD}} = \beta_{\mathrm{TTB}} = 0.30$. 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 β_{TALLY} and β_{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. Note that according to Equation A2, larger values of w represent more time needed to develop a preference for a strategy. For example, when $w = 4$ and $\beta_{\mathrm{TALLY}} = 0.8$, the initial expectancy for the TALLY strategy is 0.32 ($0.1 \times 4 \times 0.8$), whereas for TTB or WADD, it is 0.04 ($0.1 \times 4 \times 0.04$). In contrast, when $w = 40$ and $\beta_{\mathrm{TALLY}} = 0.8$, the initial expectancy for the TALLY strategy is 3.2 ($0.1 \times 40 \times 0.8$), whereas for TTB or WADD, it is 0.04 ($0.1 \times 40 \times 0.1$). Although the difference is simply one of scale ($0.32 - 0.04 = 0.28$ vs. $3.2 - 0.04 = 2.8$), it implies that in the first case, three trials of positive reinforcement are enough to overturn the relative value of strategies' expectancies (3×0.1 euro $= 0.30 > 0.28$), whereas in the second case, an almost 10-fold number of trials would be needed (29×0.1 euro > 2.8).

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 $p(a|i)$ of choosing alternative a when strategy i is selected is either $p(a|i) = 1$ or $p(a|i) = 0$ for deterministic strategies (if strategies lead to an ambiguous prediction $p(a|i) = 1/k$, with k being the number of alternatives that 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 of 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:

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

In sum, Equations A1–A5 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 β, and the application error parameter ε. Specifically, SSL predicts the probability with which a participant will choose each of the available alternatives conditioned on past choices and the received feedback.