

Older Adults Are Highly Responsive to Recent Events During Decision-Making

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Recent work suggests that older adults' decision-making behavior is highly affected by recent events. In the present work, younger and older adults performed a 2-choice task where 1 option provided a larger average reward, but there was a large amount of noise around the mean reward for each option, which led to sharp improvements or declines in rewards over trials. Older adults showed greater responsiveness to recent events than younger adults as evidenced by fits of Reinforcement Learning (RL) models. Older adults were particularly sensitive to recent negative events, which was evidenced by a strong tendency for older adults to switch to the other option following steep declines in reward. This tendency led to superior performance for older adults in 1 condition where heightened sensitivity to recent negative events was advantageous. These results extend prior work that has found an older adult bias toward negative feedback and suggest that older adults engage in more abrupt switching in response to negative outcomes than younger adults.

Keywords: aging, decision-making, reinforcement learning, reward, mathematical modeling

People of all ages must make many decisions on a daily basis, with varying degrees of uncertainty regarding the outcomes. One critical aspect in decision-making under uncertainty involves learning from the consequences, or outcomes, of each decision. Observation of long-term trends regarding which options, on average, lead to better payoffs than other competing options is a crucial aspect of decision-

making. Similarly, observation of short-term trends or abrupt changes in reward outcomes can also strongly affect decisions (Kovach et al., 2012; Otto, Markman, & Love, 2012).

Recent work has demonstrated that older adults may rely on simple heuristics during decision-making more than younger adults (Bessedes, Deck, Sarangi, & Shor, 2012; Castel, Rossi, & McGillivray, 2012; Worthy & Maddox, 2012). One commonality among these heuristics is an increased reliance on recent events. For example, older adults are more likely than younger adults to endorse the "hot-hand" heuristic in basketball, which gives greater weight to recent shot outcomes than the shooter's long-term average in determining the probability that the next shot will be made (Castel et al., 2012). Similarly, older adults are more likely to utilize a "win-stay-lose-shift" (WSLS) heuristic during decision-making tasks, which entails focusing only on changes in the most recent decision outcomes. In contrast, younger adults' behavior is better characterized by a Temporal-Difference Reinforcement Learning (Sutton & Barto,

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1998) strategy that relies on an exponentially weighted average of past rewards (Worthy & Maddox, 2012; Worthy, Otto, & Maddox, 2012).

Based on these findings, we reasoned that older adults may show enhanced sensitivity to recent events during decision-making, namely marked improvements or declines in reward for each option. In addition, we proposed that the greater attention given to recent events by older adults would be most prevalent following recent negative outcomes, or declines in reward, relative to previous trials. Supporting this prediction, a number of recent studies demonstrate that older adults learn more from negative rather than positive outcomes (Eppinger, Hammerer, & Li, 2011; Eppinger & Kray, 2011; Frank & Kong, 2008; Hämmerer, Li, Muller, & Lindenburger, 2011; Simon, Howard, & Howard, 2010). These studies utilized probabilistic reinforcement learning tasks with binary-valued outcomes where participants were told that they were either correct or incorrect on each trial. These types of tasks mirror many real-world decision-making situations where decisions can be dichotomously classified as “correct” or “incorrect.”

However, the positive and negative feedback following choices often comes in varying magnitudes, and moreover, these magnitudes fluctuate over time. For example, financial investments can result in varying amounts of gains or losses. Here, we examine whether older adults are more sensitive than younger adults to recent fluctuations in reward, and if their putative focus on negative feedback makes them more likely to switch away from an option following steep declines in reward. To test this, we had older and younger adults perform two conditions of a simple two-choice task where one option provided larger rewards, on average, than the other option, but there was a large variance around the mean reward given by each option. This led to large fluctuations in reward, affording examination of responsiveness to recent positive and negative events. We predicted that both younger and older adults would learn which option provided larger average rewards, but at the same time, older adults would attend more to recent events, particularly negative events, compared with younger adults. To test the latter prediction, we employ nuanced behavioral metrics and computational modeling to

elucidate how recent reward trends influence participants’ choices. In the first condition, termed the “consistent rewards” condition, the mean reward provided by each option remained consistent over all trials but there was noise around each option’s mean reward value. We expected older adults to be more likely to switch following steep declines in reward, relative to the selected option’s expected value. However, because these declines in reward were not indicative of longer-term trends in expected value of the choice options, we did not expect differences in overall task performance, as measured by cumulative reward earned.

To provide a corroborative test of our hypothesis, we had a second group of older and younger adults make choices in a similar task structure where switching based on recent negative events should result in better overall performance. In this “variable rewards” condition, if participants switched following a reward that was less than the current average reward provided for the option they selected they would receive a temporary “bonus” in the rewards they received for both options. This bonus was equivalent to the difference between the current average reward for the option they had selected and the reward they received prior to switching. Thus, if older adults tended to switch more following steep declines in reward then they would be temporarily rewarded with larger rewards for both options, improving their performance (see below for more detailed information). To summarize, we predicted that older adults would show similar behavior across the two conditions, where they would be more likely to switch following steep declines in reward, and that this would lead to superior performance, relative to younger adults, in the variable rewards condition.

Method

Forty-seven older adults (mean age = 67.43, $SD = 5.05$, range = 61–78) and 49 younger adults (mean age = 20.02, $SD = 1.88$, range = 18–26) were paid \$8 per hour to complete the experiment. There were 23 older adults and 25 younger adults in the consistent rewards condition, and 24 older and younger adults in the variable rewards condition.

Older adult participants were recruited through an advertisement in the local newspa-

per and through flyers posted at locations throughout the area. Younger adults were recruited from flyers and email solicitations. Our stopping rule for data collection was to recruit 25 participants in each condition and to stop when we were no longer receiving responses from interested participants.

Neuropsychological Testing Procedure

Older adults were given a series of standardized neuropsychological tests. The battery of tests was designed to assess general intellectual ability and included: Wechsler Adult Intelligence Scale–3rd edition (WAIS-III Digit Span; Wechsler, 1997); Trails Making Test A&B (TMT; Reitan, 1958); FAS (Lezak, 1995); Wisconsin Card Sorting Task (WCST; Heaton, 1981), and the California Verbal Learning Test (CVLT; Delis, Kramer, Kaplan, & Ober, 1987). The tests were administered in a single 1-hr session, in the same basic order to all subjects. The delay period for the CVLT was kept constant and was comprised of other tests not requiring any long term memory storage.

The standard, age appropriate, published norms were used to calculate normative scores for each subject. Table 1 shows the means, *SDs*, and ranges of standardized *z*-scores on each test for older adult participants in the study. For the WAIS digit-span test, the percentile was calculated according to testing instructions, and this score was then converted to a standardized *z*-score. For the CVLT and WCST, standardized *T* scores were calculated according to testing directions, and this score was then converted to a standardized *z*-score. Finally, for the TMT, standard *z*-scores were calculated according to

the testing instructions. There were no subjects 2 *SDs* below the standardized mean on more than two neuropsychological tests. The neuropsychological testing session was held before the experimental session, and only participants who were within normal ranges were asked to participate in the experiment.

Decision-Making Task Procedure

Participants were given a cover story that they were astronauts on Mars testing two systems that extracted oxygen from the Martian atmosphere (Figure 1a). Their goal was to extract as much oxygen as possible. In the consistent rewards Condition System A extracted a mean of 65 units of oxygen per trial, while System B extracted a mean of only 55 units of oxygen per trial (Figure 1b). The *SD* around each system's mean payoff was 10 units.¹ Thus, while System A yielded more reward on average than System B, both options' rewards' exhibited large variance.

In the variable rewards condition both options provided the same rewards, and an additional value, ε , was added to the mean rewards for each option from the consistent rewards condition. The quantity ε changed the average rewards provided by each option from the consistent rewards condition, serving as a bonus when positive, and a penalty when negative. The ε value was initialized at 0 and updated each time participants switched to a different option according to:

$$\begin{aligned} \varepsilon_t &= \bar{X}_{r,i,t-1} + \varepsilon_{t-1} - r_{t-1}, \\ &\text{if } \text{choice}_t \neq \text{choice}_{t-1}; \\ &\text{otherwise, } \varepsilon_t = \varepsilon_{t-1} \end{aligned} \quad (1)$$

where $\bar{X}_{r,i,t-1}$ is the mean reward value from the consistent rewards condition for the chosen option, *i*, on the preceding trial and r_{t-1} is the reward that was received on the previous trial. Thus, ε was positively incremented if participants switched following rewards that were less than the current average, and negatively incremented if

¹ Rewards were sampled using Matlab's *normrnd* function, which provides random arrays from a normal distribution. The actual observed values for System 1 were ($M = 54.12$, $SD = 9.82$), and for System 2 were ($M = 65.84$, $SD = 10.70$).

Table 1
Average Scores on Neuropsychological Tests

Neuropsychological test	<i>M</i> (<i>SD</i>)	Range
Digit span	0.45 (.91)	-1.3 to 2.5
Trails A	-.14 (.81)	-1.75 to 1.61
Trails B	-.23 (.72)	-1.54 to 2.5
F-A-S verbal fluency test	-.21 (.83)	-1.81 to 2.15
WCST Errors	.75 (1.35)	-2.3 to 2.5
WCST Perseveration	.80 (1.07)	-1.9 to 2.5
CVLT Immediate Recall	.63 (1.02)	-1.5 to 2.5
CVLT Delayed Recall	0.31 (.94)	-1.5 to 2.00

Note. WCST = Wisconsin Card Sorting Task; CVLT = California Verbal Learning Test.

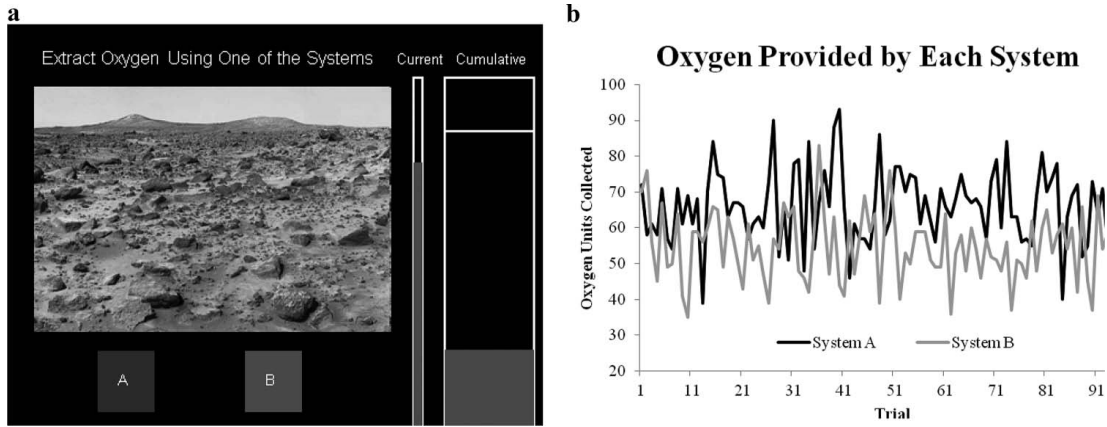


Figure 1. (a) Sample screen-shot from the experiment. (b) Rewards provided by each option in the consistent rewards condition. In the variable rewards condition, the rewards shown were provided in addition to the bonus amount (ε) given by Equation 1.

participants switched following rewards that were greater than the current average. Note that if recent events had no effect on participants' switching behavior then the amount of oxygen collected in the consistent and variable rewards conditions should be equivalent.

In both conditions, participants accumulated oxygen by selecting either system on each of 100 trials. They were not told anything about the rewards they could expect to see from each option, but had to learn from experience. In the consistent condition participants were given a goal equivalent to extracting 6,300 units of oxygen by end of the experiment. This was roughly equivalent to what would be achieved by selecting System A on 80% of trials, whereas in the variable condition the goal was equivalent to extracting 7,000 units of oxygen as we predicted that participants would collect more oxygen because of the addition of the bonus amount.

On each trial participants selected one of two systems and a small oxygen meter on the right-hand side of the screen filled up a certain amount in blue representing the amount of oxygen that had just been extracted. The oxygen was then transferred into a larger tank representing the amount they had cumulatively extracted (Figure 1a). At the end of the experiment participants were told whether or not they reached their goal and thanked for their participation. We did not include any additional measures or experimental conditions other than what are reported below.

Results

Figure 2a shows the average cumulative reward for participants in each condition. A 2 (Age) \times 2 (Condition) analysis of variance (ANOVA) revealed a significant effect of age,

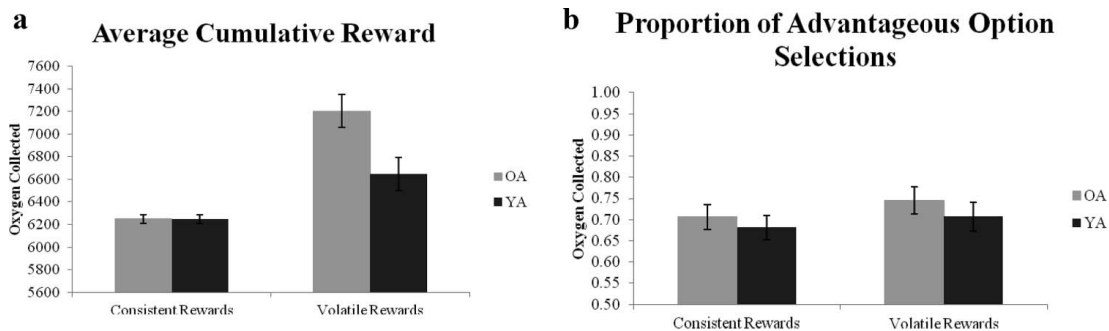


Figure 2. (a) Average cumulative amount of oxygen gathered for participants in each group. (b) Average proportion of System A selections. Error bars represent SEMs.

$F(1, 92) = 6.87, p < .01, \eta^2 = .069$, a significant effect of condition, $F(1, 92) = 40.39, p < .001, \eta^2 = .305$, and a Significant Age \times Condition interaction, $F(1, 92) = 6.83, p < .01, \eta^2 = .069$. Pairwise comparisons between older and younger adults within each experimental condition revealed no effect of age on performance within the consistent rewards condition, $t(46) = .016, p = .99$ (older adults $M = 6,249, SD = 175$; younger adults $M = 6,248, SD = 189$), but a significant effect of age on performance within the variable rewards condition, $t(46) = 2.70, p < .01$ (older adults $M = 7,203, SD = 711$; younger adults $M = 6,646, SD = 718$).

We also examined the proportion of trials that participants selected System A, the advantageous option (Figure 2b). There was no main effect for age ($F < 1$) or condition ($F = 1.14$) and no Age \times Condition interaction ($F < 1$). Thus, the superior performance for older adults in the variable rewards condition was not simply because of their selecting the better option more often than younger adults.

Next, we fit each participant's data individually with a Basic and Expanded version of a Reinforcement-Learning (RL) model to investigate the degree to which participants utilized recent and long-term reward outcomes. RL models have proven to be a valuable tool in much prior work for conducting more thorough analyses of decision-making behavior (e.g., Busemeyer & Stout, 2002; Worthy, Maddox, & Markman, 2007; Yechiam & Busemeyer, 2005).

The models both assumed that the expected value (V) for each option is an exponentially weighted average of the rewards that have been received after selecting each option. V s for all options were initialized at 60 units which is the midpoint between the average rewards provided by each option. V s were updated only for the chosen option, i , based on the prediction error (δ_i), which represents the difference between the reward received (r_i) and the expected reward value:

$$\delta_t = r_t - V_t(i) \quad (2)$$

For the Basic RL model, the expected value for the chosen option (V_i) was then updated according to the following updating rule:

$$V_{t+1}(i) + \alpha \cdot \delta \quad (3)$$

Learning is modulated by a learning rate parameter (α), $0 \leq \alpha \leq 1$ that weighs the degree to which the model updates the V s for each option based on the prediction error (δ). As α approaches 1 greater weight is given to the most recent rewards in updating V s, and as α approaches 0 recent rewards are given less weight.

The Expanded version of the RL model also used Equation 3 to update expected values but the model included separate learning rate parameters for trials with positive (α_{pos}) and negative (α_{neg}) prediction errors. The inclusion of separate learning rate parameters for positive and negative prediction errors allows the model to account for participants tendencies to update expected values at different rates following positive or negative trends. The Expanded RL model's ability to differentially weigh positive and negative prediction errors echoes prominent cognitive learning models (e.g., the Expectancy Valence and Prospect Valence Learning models; Ahn, Busemeyer, Wagenmakers, & Stout, 2008; Busemeyer & Stout, 2002), which allow for different weighting of gains versus losses, and is further supported by biological dissociation of these weightings (Frank, Moustafa, Haughey, Curran, & Hutchison, 2007; Frank, Doll, Oas-Terpstra, & Moreno, 2009).

We also included an autocorrelation term (A) in both models that accounts for any autocorrelation in choices not explained by changes in reward (Daw, 2011; Lau & Glimcher, 2005).² The recent selection term for option i is simply 1 if that option was chosen on the previous trial, and 0 otherwise:

$$A_{t+1}(i) = \begin{cases} 1, & \text{if } a_t = i \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

This term models the tendency to switch or stay with the same option regardless of the payoffs received.

Choice Rule

The probability for selecting each option is determined by a Softmax rule that includes the

² See also Otto, Markman, Gureckis, and Love (2010) for an alternative method of accounting for autocorrelation that was affected by a manipulation of motivational state.

value (V), and autocorrelation terms (A) for each option.

$$P(a_t = i) = \frac{e^{[\beta_V \cdot V_t(i) + \beta_A \cdot A_t(i)]}}{\sum_{j=1}^2 e^{[\beta_V \cdot V_t(j) + \beta_A \cdot A_t(j)]}} \quad (5)$$

Here inverse temperature parameters, β_V , and β_A , weight the degree to which the value (V) and autocorrelation terms (A) terms contribute to each choice.

Model Comparison

The RL models' fits were assessed based on their ability to predict each choice a participant would make on the next trial, by estimating parameter values that maximized the log-likelihood of each model given the participant's choices. To avoid recovering parameters at local minima, we fit each model with 500 random starting points.

The Basic RL model was nested within the Expanded RL model as a special case when α_{pos} is equivalent to α_{neg} . Accordingly, we first used a likelihood ratio test to assess whether the addition of a second learning rate parameter significantly improved the fit. The G^2 statistic, which is twice the difference in log-likelihood between each model follows a χ^2 distribution, with df equal to the difference in the number of free parameters for each model (Maddox & Ashby, 1993):

$$G^2 = 2 \cdot [LL_{\text{Expanded}} - LL_{\text{Basic}}] \quad (6)$$

The G^2 (likelihood ratio) test evaluates the contribution of the additional learning rate parameter in the Expanded Model (Kovach et al., 2012; McCullagh & Nelder, 1999).

To compare the Expanded RL model with the nested Basic RL model within younger and older adults, we summed the G^2 values over all participants in each group, with df equal to the number of participants in each group (Daw, 2011; Kovach et al., 2012). The full model provided a better description than the nested model within both the consistent rewards ($p < .01$, $df = 48$) and variable rewards conditions ($p < .01$, $df = 48$).

As a second method of comparing the fit of each model we computed each model's Bayesian Information Criterion (BIC; Schwarz, 1978):

$$BIC = -2 \cdot LL_{\text{Model}} + k \cdot \ln(N) \quad (7)$$

Here k equals the difference in the number parameters between the models and N equals the number of observations. Positive values indicate a better fit for the RL model and negative values indicate a better fit for the Baseline model. BIC is one of the more conservative methods for evaluating models because of its harsher penalization of models with additional free parameters compared with other methods like the likelihood ratio test presented previously (Collins & Frank, 2012; Vrieze, 2012; Wagenmakers & Farrell, 2004).

We also fit a Baseline model that assumed stochastic responding. This model had one free parameter that represented participants' tendencies to select System A on each trial, regardless of their recent choice history (Yechiam & Busemeyer, 2005).

Table 2 lists the average log-likelihood and BIC values for each model for each group of participants. Both of the RL models provided a better fit than the Baseline model for all groups. The inclusion of an additional learning rate parameter in the Extended RL model resulted in a very small improvement in log-likelihood. Average BIC values were lower for the Basic RL model than for the Extended RL model for each group of participants, suggesting that the Extended model did not provide a significantly improved fit, according to BIC. Thus, while the results of the G^2 likelihood ratio test indicated that the addition of a second learning rate parameter in the Extended RL model significantly improved the fit, the more conservative BIC comparison suggested that the improvement in fit was a modest one.

As a second method of evaluating the ability of the RL models to account for behavior in the task, we performed simulations of each task using participants' best-fitting parameter estimates. This has become an increasingly common additional check for how well computational models account for behavior (e.g., Steingroever, Wetzels, & Wagenmakers, 2013; Worthy, Pang, & Byrne, 2013; Worthy, Hawthorne, & Otto, 2013). For both models, we performed 1,000 simulations for each task for both older and younger adults by randomly sampling with replacement a set of parameter values for each simulation. We then computed

Table 2
Average Log-Likelihood and Bayesian Information Criterion (BIC) Values for Each Reinforcement Learning (RL) Model

Variable	Younger adults	Older adults
Consistent rewards condition		
Log-likelihood		
Basic RL model	45.81 (16.04)	41.08 (15.93)
Extended RL model	44.84 (15.59)	40.51 (16.14)
Baseline model	57.71 (12.76)	55.83 (14.03)
BIC		
Basic RL model	105.46 (32.08)	95.98 (31.86)
Extended RL model	108.11 (33.18)	99.45 (32.28)
Baseline model	120.02 (25.52)	116.27 (28.08)
Variable rewards condition		
Log-likelihood		
Basic RL model	38.34 (20.22)	30.99 (19.00)
Extended RL model	36.62 (21.29)	30.16 (18.74)
Baseline model	53.40 (18.49)	49.52 (20.49)
BIC		
Basic RL model	90.50 (40.44)	75.79 (38.00)
Extended RL model	91.66 (42.58)	78.75 (37.48)
Baseline model	111.40 (36.98)	103.65 (40.98)

Note. SDs are listed in parentheses.

the points earned in 25-trial blocks in the task and compared the average points earned by participants. Figure 3 shows the simulation results for the Basic (Figure 3a) and Extended (Figure 3b) RL models for the consistent rewards condition and Figure 4 shows the same results for the variable rewards condition. Both models are able to simulate performance that is highly similar to the performance of our participants.³ For both models, the simulations predict better performance for older than for younger adults in the variable rewards condition, although both models slightly overpredict performance for younger adults and underpredict performance for older adults.

As a final test of the RL models we used the Generalization Criterion Method (Ahn et al., 2008; Busemeyer & Wang, 2000; Yechiam & Busemeyer, 2005; Yechiam & Busemeyer, 2008) to assess the ability of each model to predict behavior in one condition (a generalization condition) using parameter estimates from participants who performed in another condition (a calibration condition). We had the consistent rewards condition represent the calibration condition and the variable rewards condition represent the generalization condition. Using parameter estimates from the consistent rewards condition, we conducted 1,000

simulations in the variable rewards condition for each model and for both younger and older adults. Next we computed the mean squared error (*MSE*) between the average points earned by participants on each trial and the average points earned across all simulated trials. Lower values indicate a more reliable prediction for the amount of points participants earned on each trial. The *MSE* values for each model are listed in Table 3. These values are lower for the Basic RL model than for the Extended model for both younger and older adults which suggests parameter estimates from the simpler model may be more reliable as predictors for different tasks.

Best-Fitting Parameter Values

We next examined the estimated parameter values for younger and older adults. We first examined differences across both conditions and then within each condition (Table 4). Across both conditions a Mann–Whitney *U* test

³ The decline in cumulative reward during block 4 for both participants and the models is likely because of the Advantageous option providing smaller rewards on average during block 4 ($M = 64.5$ units) than in blocks 2 ($M = 67.1$ units) and 3 ($M = 68.5$ units). Thus, the decline was at least partially attributable to sampling error in the reward distributions.

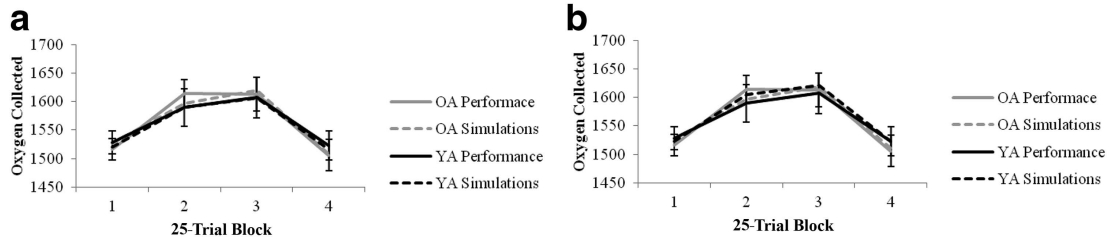


Figure 3. (a) Simulation results for the Basic Reinforcement Learning (RL) model in the consistent rewards condition. (b) Simulation results for the Extended RL model in the consistent rewards condition. Error bars represent 95% confidence intervals.

revealed a significant difference in α for the Basic RL model, $U = 746.00, p < .01$. For the Extended RL model older adults had significantly larger α_{pos} values than younger adults, $U = 859.00, p < .05$, and significantly larger α_{neg} values, $U = 584.50, p < .001$. There were no age group differences in the value or autocorrelation inverse temperature parameters (all $p > .10$).

Within the consistent rewards Condition Mann–Whitney U tests revealed a significant difference between groups in α for the Basic RL model, $U = 165.50, p < .05$. For the Extended RL model older adults had significantly larger α_{neg} values than younger adults, $U = 135.00, p < .01$, suggesting that recent negative events exerted greater influence on this group’s choices. However, while older adults’ data were also best fit by larger α_{pos} values, the difference was not reliable, $U = 200.00, p = .052$.

Within the variable rewards condition older adults’ data were best fit by larger α values for the Basic RL model, although the difference did not reach significance, $U = 212.00, p = .115$. For the Extended RL model there was no age difference in estimated α_{pos} values, $U = 226.00, p = .182$, but there was a

significant age difference in estimated α_{neg} values, $U = 151.50, p < .01$. We also examined whether larger estimated α_{neg} values predicted better performance in this condition. A simultaneous regression with all four of the parameters for the Extended RL model entered as predictors and total cumulative points entered as the outcome variable revealed that estimated α_{neg} values predicted better performance on the task, $\beta = .34, p < .05$. However, there was no relationship between α_{pos} values and performance, $\beta = .11, p = .53$.

Prediction Errors Preceding Stay and Switch Trials

Next we examined prediction errors (δ) on trials that preceded “stay” and “switch” trials to examine responsiveness to recent events, corroborating the results of the modeling analysis. Because the Basic RL model provided a better fit to the data based on the more conservative BIC criterion and based on the results of the Generalization Criterion method test, we used the average best-fitting α value from the Basic RL model across both age groups to update

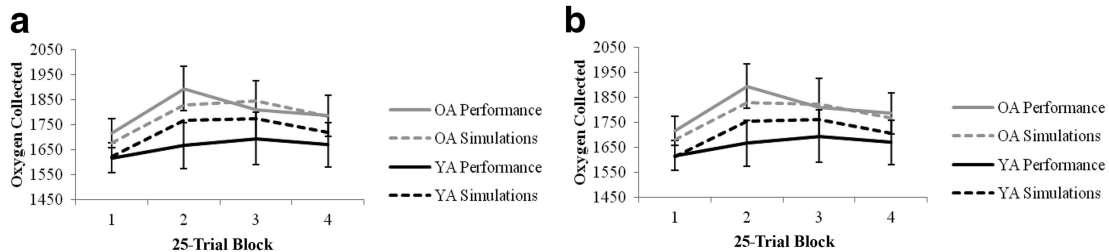


Figure 4. (a) Simulation results for the Basic Reinforcement Learning (RL) model in the variable rewards condition. (b) Simulation results for the Extended RL model in the variable rewards condition. Error bars represent 95% confidence intervals.

Table 3
*Mean Squared Error (MSE) Values From the
 Generalization Criterion Method*

Model	Younger adults	Older adults
Basic RL	7.14	8.69
Extended RL	11.60	9.52

Note. RL = Reinforcement Learning.

expected values. Prediction errors were computed as in Equation 2.⁴ Intuitively, a decision-maker sensitive to recent negative events would be more likely to switch from selecting a currently favored option after observing large negative prediction errors. To test this possibility, we assessed whether average prediction errors differed between groups on stay and switch trials.

Figure 5 depicts the average prediction errors on stay and switch trials for the option that was chosen on the previous trial. A 2 (age) \times 2 (condition) \times 2 (trial-type) repeated measures ANOVA showed a main effect of trial-type, $F(1, 92) = 63.51, p < .001, \eta^2 = .408$, a significant effect of age, $F(1, 92) = 15.31, p < .001, \eta^2 = .143$, and a Significant age \times Trial-type interaction, $F(1, 92) = 9.98, p < .01, \eta^2 = .098$. There was no difference between age groups in average prediction errors on trials that preceded stay trials, $t(94) = .76, p = .45$, but average prediction errors on trials preceding switch trials differed significantly between groups, $t(94) = -3.65, p < .001$. Prediction errors for trials preceding switch trials were significantly larger in magnitude for older adults ($M = -5.71, SD = 4.97$) than for younger adults ($M = -2.26, SD = 4.28$). The age difference was significant within both the consistent rewards condition, $t(46) = -3.29, p < .01$, and the variable rewards condition, $t(46) = -2.05, p < .05$.

Discussion

Our results provide support for the hypothesis that older adults' choice behavior is more responsive to recent events than that of younger adults. Despite no age-group differences in the proportion of times participants selected each option, older adults performed better in the variable rewards condition, where switching following steep declines in reward was advanta-

geous. The computational modeling and average prediction error analyses revealed further evidence of age-based differences in responses to recent events during decision-making. Older adults utilized recent reward information to a significantly greater extent than younger adults in evaluating each option. These differences were most noticeable following large negative decreases in rewards, where older adults tended to shift immediately to the other option, while younger adults' switches were not related to as steep of declines in reward.

There is emerging evidence that older adults learn more from negative than from positive feedback during learning and decision-making (Eppinger et al., 2011; Eppinger & Kray, 2011; Frank & Kong, 2008; Hämmerer et al., 2011; Simon et al., 2010). Our results suggest that this focus on negative feedback extends to *relative* declines in reward magnitudes in addition to binary feedback (e.g., incorrect vs. correct, or loss vs. no loss). However, it is important to note that our modeling results suggest that older adults were more sensitive negative trends overall, regardless of the valence.

However, changes in responsiveness to positive versus negative information that accompany healthy aging has been the source of some debate, with evidence of reduced brain activity in older adults in regions implicated in reward-based decision making when anticipating monetary losses, but not when anticipating monetary gains (Samanez-Larkin et al., 2007). Other work has found evidence for heightened anticipatory skin-conductance responses in high-performing older adults when selecting the advantageous options, which have net positive outcomes over trials, during the Iowa Gambling Task (Denburg, Tranel, & Bechara, 2005; Wood et al., 2005). In addition, a prominent theory of how aging affects socioemotional functioning suggests that older adults focus on positive rather than negative cues in their environment (Carstensen, 1992). One explanation for these conflicting findings is that older adults may focus more on the positive aspects of their decisions when anticipating the outcomes, but

⁴ We also conducted the same analysis using several different values for α and the same general pattern shown in Figure 5 was observed regardless of what the α value was.

Table 4
Average Best-Fitting Parameter Values for Each Reinforcement Learning (RL) Model

Variable	Younger adults	Older adults
Consistent rewards condition		
Basic RL model		
Learning rate (α)	.48 (.43)*	.73 (.36)*
Value inverse temperature (β_v)	2.12 (4.02)*	.12 (.15)*
Autocorrelation inverse temperature (β_A)	.45 (1.06)	.63 (.96)
Extended RL model		
Positive learning rate (α_{pos})	.55 (.48)	.74 (.42)
Negative learning rate (α_{neg})	.32 (.41)*	.61 (.41)*
Value inverse temperature (β_v)	3.38 (4.53)*	1.12 (2.91)*
Autocorrelation inverse temperature (β_A)	.47 (1.10)	.63 (1.02)
Variable rewards condition		
Basic RL model		
Learning rate (α)	.45 (.37)	.63 (.45)
Value inverse temperature (β_v)	1.63 (3.55)	1.22 (3.01)
Autocorrelation inverse temperature (β_A)	.74 (2.36)	.56 (2.21)
Extended RL model		
Positive learning rate (α_{pos})	.54 (.44)	.70 (.40)
Negative learning rate (α_{neg})	.33 (.39)**	.65 (.38)**
Value inverse temperature (β_v)	2.14 (3.90)	.80 (2.35)
Autocorrelation inverse temperature (β_A)	.12 (2.46)	.32 (2.37)

Note. SDs are listed in parentheses.

* Significant age group difference at $p < .05$ level. ** Significant age group difference at $p < .01$ level.

focus more on negative information when processing feedback or evaluating the outcomes of their decisions (Eppinger et al., 2011; Eppinger, Kray, Mock, & Mecklinger, 2008).

In addition, these results are not necessarily inconsistent with the extensive evidence for the “positivity effect” in older adults, whereby they engage in emotion regulation mechanisms to enhance memories for positive information and diminish memories for negative information (Mather & Carstensen, 2005). One interpretation of our finding that older adults tend to shift to a different option following sharp drops in

reward is that older adults have a heightened tendency to avoid the possibility of selecting an option that is declining in value. This may be related to their tendency for stronger regulation against negative information.

While the present results reveal that older adults are more sensitive to recent negative events, future work is needed to pinpoint possible mechanisms underlying this apparent age difference. One prominent neurobiological theory proposes that the enhanced responsiveness to negative feedback in older adults is at least partially because of age-related declines in dopamine levels, which enhance learning from negative outcomes (Frank & Kong, 2008). In addition, working memory impairments are known to accompany older age, which may be responsible for older adults’ reliance on more recent reward outcomes (Rypma & D’Esposito, 2000). However, our study did not directly address the link between working memory and decision-making behavior. Future work could examine this relationship and whether certain experimental manipulations might decrease older adults’ reliance on recent information.

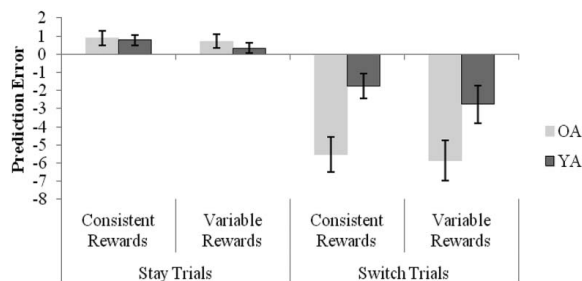


Figure 5. Average prediction errors on trials preceded by stay and switch trials. Error bars represent SEMs.

This work also highlights the importance of applying computational models to behavioral data, particularly for special populations (e.g., Busemeyer & Stout, 2002; Yechiam, Busemeyer, Stout, & Bechara, 2005). Decision-making is a complex task and gross measures of performance are often inadequate for providing a full account of behavior. We found that utilization of a Basic RL model, combined with more nuanced behavioral metrics uncovered a robust age-related difference in responsiveness to recent events.

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