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Decision-making strategies and performance among seniors☆

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ABSTRACT

Using paper and pencil experiments administered in senior centers, we examine decision-making performance in multi-attribute decision problems. We differentiate the effects of declining cognitive performance and changing cognitive process on decision-making performance of seniors as they age. We find a significant decline in performance with age due to reduced reliance on common heuristics and increased decision-making randomness among our oldest subjects. However, we find that increasing the number of options in a decision problem increases the number of heuristics brought to the task. This challenges the choice overload view that people give up when confronted with too much choice.

1. Introduction

Virtually all consumer choices, be they among retirement savings plans, health care plans, or brands of shampoo, involve choosing among alternatives characterized by sets of attributes. An extensive literature demonstrates that the quality of and satisfaction with choices generally decline as the number of options increases (e.g., Payne et al., 1993; Iyengar and Lepper, 2000; Tanius et al., 2009; Schram and Sonnemans, 2011; Hanoch et al., 2011). Researchers have hypothesized that this effect is due to *choice overload*; when facing a multitude of options, "rather than even try, people may disengage, choosing almost arbitrarily" (Schwartz et al., 2002, p. 1179). Recently, Besedeš et al. (2010) measured decision-making accuracy in complex tasks in an online experiment and confirmed that decision-making performance decreases as the number of available options increases. They also report that older subjects use suboptimal problem-solving approaches, or heuristics, when compared to younger subjects, leading to objectively worse choices with age.

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Past work has shown two contrasting effects of aging on decision-making. First, cognitive functions physically decline with age (Cerella, 1985; Mittenberg et al., 1989; Zimprich and Martin, 2002; Gilchrist et al., 2008; Goldberg, 2009). Second, older individuals employ different heuristics in their approach to solving problems (Cole and Balasubramanian, 1993; Johnson, 1993; Yoon et al., 2009). For example, seniors generally consider a smaller information set prior to making decisions and rely more on deductive than on inductive strategies as compared to younger people (Meyer et al., 1995; Zwahr et al., 1999). Neurologically, seniors involve both hemispheres of the brain in decision making, unlike younger adults who generally use either the left or the right side depending on the task (Cabeza, 2002). Despite cognitive decline, these heuristic adaptations can lead to improved performance with age in some cases (Stern and Carstensen, 2000; Scheibe and Blanchard-Fields, 2009).

We present the results of a paper and pencil experiment conducted at senior citizen activity centers in Baton Rouge, Louisiana. Subjects completed a series of choice tasks where they were presented with several options and asked to select one. Each option contained several attributes each corresponding to a probability of receiving a payment, thus enabling us to evaluate objectively the relative quality of a subject's choices. While the experimental design we use in this paper is similar to that of Besedeš et al. (2010), this paper is distinguished by its singular focus on decision-making strategies of seniors and how they evolve both with age and the number of options in the choice set. Thus, the objective of this paper is twofold. First, we examine the effects of declining cognitive performance and changing cognitive process on decision-making performance of seniors as they age. Second, we test the behavioral hypothesis of choice overload, examining whether seniors give up when facing too many options. Another important distinction between this paper and Besedeš et al. (2010) is our use of in-person experiments which may provide a more representative sample of seniors than their online experiments.

Our data suggest that younger seniors-people between the age of 60 and 75-perform substantially better than those over the age of 75. Younger seniors also employ a wide array of problem-solving strategies. With increasing age, we find a decline in performance and a reliance on fewer problem-solving strategies, with the oldest subjects exhibiting a significant random component in decision making.

However, among seniors as a whole, we find a moderating effect of increasing the number of options. Rather than suffering from choice overload and simply leaving a choice to chance when faced with a multitude of options, seniors incorporate *more* heuristics as task complexity increases. While seniors are less likely to identify the best option from an increasing number of options, they are substantially *more* likely to identify a good option, defined as the top quartile of all options. We find that increased choice complexity leads to a reliance on a greater number of heuristic strategies, consistent with subjects attempting to eliminate the worst choices from further consideration.

2. Experiment design

Subjects participated in a series of 19 decision tasks. In each task, subjects are asked to select one option from among a number of options that is most likely to include a single randomly selected attribute. Attributes are denoted as colored balls, with the frequency distribution among colored balls given for each task. For example, Fig. 1 illustrates a 4-option 4-attribute choice task. Options can be thought of as health insurance or drug coverage plans, while attributes can be thought of as health conditions (diseases) or particular drugs where the probability associated with an attribute gives the likelihood of being struck with a particular condition or requiring a particular drug. In the example in Fig. 1, an urn would be filled with 100 colored balls: 28 lime, 24 pink, 26 white, and 22 green. One randomly drawn ball would determine whether the subject receives $50 if the selected option includes the drawn attribute or $15 if it does not. In this case, option A is the best choice; it includes the lime, pink, and green attributes, for a total of 74 of the 100 balls and thus a 74 percent chance of earning the larger payoff. This design ensures that all individuals have the same preferences over options, governed by the total probability of payment.

The experiment was conducted in three centers operated by the Recreation and Park Commission for the Parish of East Baton Rouge (BREC) which facilitates various programs and activities for seniors. Fliers were posted throughout the centers operated by BREC advertising the experiment. One session was conducted at each BREC center with all of the subjects participating in a session seated in a single large room and observing the same urn draw. All sessions were administered by the same research assistant who read the instructions aloud, addressed any questions subjects had prior to the experiment, collected task booklets and surveys, and administered payments.

Each subject was presented with a choice booklet and a survey booklet. Once subjects selected an option in each task, one task was randomly selected to determine the subject's payment. Nineteen identical pieces of paper with task numbers

BALLS	#	OPTIONS Circle the letter option of your choice.			
		A	B	C	D
Lime	28	✓		✓	
Pink	24	✓			
White	26		✓		✓
Green	22	✓	✓	✓	

Fig. 1. Sample choice task.

written on them were placed in an urn and one was drawn by a BREC representative who was present throughout the experiment. Then, colored balls corresponding to the chosen task were counted out and placed in the urn. The urn had an opening which allowed only one ball to fall out at a time. Once filled with the proper combination of colored balls, the urn was shaken and turned upside down to draw one ball. Each subject was initially endowed with \$50. If the color of the drawn ball was included among the attributes of the subject's chosen option, the subject did not incur a loss. Otherwise, the subject incurred a loss of \$35. As the experiment was conducted in a loss frame, our subjects were essentially choosing among insurance plans (or prescription drug plans) that completely covered some events (or medications) but not others.

The task booklet began with one simple task designed to familiarize subjects with the experiment and answer any remaining questions. This was followed by the 18 main tasks constituting a $3 \times 3 \times 2$ within-subject design. The first dimension denotes the number of options (4, 8, or 12), the second denotes the number of attributes (4, 8, or 12 colors of balls), and the third denotes the probability distribution over attributes. Presumably, the value of having more choice is the greater likelihood of a better option. Thus, the best option had a higher payoff in tasks with more options. Under the first probability distribution, PDF 1, which maintains similar probabilities for each attribute, the best option improves slightly, from a payoff of 74 to 76 to 78, as the number of options increases from 4 to 8 to 12. Under PDF 2, which has some attributes associated with substantially higher probability than others, the best option improves from a payoff of 56 to 81 to 92.

The addition of attributes preserves the expected payoff of each option, thus providing additional detail while not affecting the substance of the decision itself. This is achieved by splitting the probability of existing attributes. For example, 28 "lime" balls in the 4-attribute case could be divided into 18 lime and 10 purple balls, where options that did (not) cover lime in the 4-attribute case do (not) cover lime and purple. The full experimental design is presented in Table 1, while the appendix shows the instructions.[1]

Three versions of the choice booklet varied the order of the 18 tasks. Each task was presented on a separate page. Subjects were instructed not to go backwards in the booklet and compliance was monitored. After completing the tasks, subjects were instructed to close their task booklet and proceed to the survey booklet. The survey collected information on demographics, risky behavior, analytical ability, and experience. A total of 65 subjects participated in the hour-long experiment. Since each subject faced 18 tasks, we should observe a total of 1170 decisions. However, nine subjects failed to record decisions in a total of 15 tasks, resulting in 1155 decisions. In all reported results, omitted decisions are dropped from the analysis; in regressions, we used subject-level weights so that each subject's decisions received the same weight even if subjects did not make the same number of decisions.[2]

3. Results

We begin with a summary of performance by both demographics and task characteristics in Table 2. We examine performance across several demographic groups defined by age quartiles (60–67, 68–74, 75–79, or 80+ years), education (high school only, some college or college degree, or post-graduate education), sex, race, income (median split of less/more than \$40k) and number of children (median split of 0–3 or >4). The first column presents the frequency with which subjects selected the optimal option.

Subjects in the two youngest age quartiles select the optimal option in nearly half of all tasks. Subjects over 75 years of age do significantly worse, selecting the optimal option about one quarter of the time. The likelihood of selecting the optimal option increases with education, and is generally lower for African American subjects. Sex, income, and the number of children have negligible effects on the frequency of selecting the optimal option. Task characteristics indicate that the frequency of optimal choice declines with task complexity. Increasing either the number of options or the number of attributes leads to a reduced likelihood of selecting the optimal option. Additionally, PDF 1 encourages better decisions than PDF 2.

Less frequent selection of the optimal option as the number of options increases is not surprising. Any random component to the decision-making process would yield a 25 percent chance of identifying the optimal option in the 4-option case, but only an 8 percent chance in the 12-option case. The second column of Table 2 examines the likelihood of selecting a *Good* option, which we define as an option in the top 25 percent of the choice set (1 of 4, 2 of 8, or 3 of 12). Overall, these *Good* options have an average expected payoff in the experiment of \$36.50, while the remaining options have an expected payoff of \$21.50. Additionally, the worst *Good* option has an expected payoff that is \$6 higher than the next-best option. The frequency of selecting a *Good* option exhibits very similar demographic effects to the selection of the optimal option, decreasing with age and increasing with education. Under random decision making, the frequency of selecting a *Good* option would remain constant at 25 percent as the number of options increases from 4 to 8 to 12. However, we find that subjects selected a *Good* option with an *increasing* frequency as the number of options increases, from 46 percent with four options to 61 percent with 12 options. This argues against choice overload.

[1] The survey instrument is available on request.

[2] All our results are robust to several alternative approaches to skipped decisions. We examined exclusion of those decisions, exclusion of subjects who skipped any decision, and various coding of skipped decisions. These approaches have only marginal impacts on the presented parameters, and do not change our results qualitatively.

Table 1
Complete experimental design.

Attributes			PDF1			PDF2			12 Options											
									8 Options											
4	8	12	Number of Attributes			Number of Attributes			4 Options											
			4	8	12	4	8	12	A	B	C	D	E	F	G	H	I	J	K	L
Lime	Lime	Lime	8	2	2	28	7	7	✓		✓				✓	✓		✓		✓
	Purple	Purple		6	3		21	5	✓		✓				✓	✓		✓		✓
		Orange			2			7	✓		✓				✓	✓		✓		✓
		Lt Blue			1			9	✓		✓				✓	✓		✓		✓
Pink	Pink	Pink	36	22	18	24	11	6	✓				✓	✓			✓	✓	✓	✓
		Yellow			4			5	✓				✓	✓			✓	✓	✓	✓
	Blue	Blue		14	14		13	13	✓				✓	✓			✓	✓	✓	✓
White	White	White	45	11	11	26	8	8		✓		✓	✓		✓	✓			✓	✓
	Brown	Brown		34	19		18	7		✓		✓	✓		✓	✓			✓	✓
		Red			15			11		✓		✓	✓		✓	✓			✓	✓
Green	Green	Green	11	8	8	22	13	13	✓	✓	✓				✓		✓		✓	
	Navy	Navy		3	3		9	9	✓	✓	✓				✓		✓		✓	
							Option payoffs	PDF1	55	56	19	45	81	36	64	53	47	44	92	89
								PDF2	74	48	50	26	50	24	76	54	46	52	72	78

Table 2
Choice frequency and efficiency.

Overall		Optimal option	Good option (in top 25%)	Efficiency	*N*
		38%	58%	51%	65
By demographic characteristics					
Age	60–67	48%	66%	60%	17
	68–74	48%	69%	68%	17
	75–79	26%	46%	38%	15
	80+	29%	48%	36%	16
Education	At most high school	28%	47%	33%	22
	Some college or degree	40%	60%	54%	28
	Graduate education	52%	72%	73%	15
Sex	Female	37%	59%	52%	48
	Male	41%	56%	49%	17
Race	African-American	30%	49%	43%	11
	White and other	40%	60%	53%	54
Income	Less than 40k	39%	60%	54%	38
	Income more than 40k	36%	55%	48%	27
Children	Three or fewer	37%	57%	49%	39
	More than three	40%	59%	54%	26
By task characteristics					
Options	4	46%	46%	51%	65
	8	35%	66%	50%	65
	12	34%	61%	52%	65
Attributes	4	43%	59%	53%	65
	8	36%	57%	49%	65
	12	36%	58%	51%	65
PDFs	1	47%	66%	58%	65
	2	30%	49%	44%	65

We next examine whether choices are closer to random or optimal decision-making. The expected payoffs of chosen options are not directly comparable across different tasks as the number and quality of options varies. We define a standardized measure of decision efficiency as:

$$\text{efficiency} = \frac{\text{expected payoff of chosen option} - \text{average expected payoff of all options}}{\text{expected payoff of optimal option} - \text{average expected payoff of all options}}$$

Thus, efficiency equals 0 if the subject's expected payoff is equal to what would be yielded by a random choice and equals 1 if the maximum expected payoff is achieved. Overall, younger seniors achieve above 60 percent efficiency, while older seniors are below 40 percent. This implies that the payoffs of older seniors are closer to random choice than to optimal choice. We find little effect on efficiency of increasing task complexity, either through more options or attributes. Thus, while we find evidence that older subjects are closer to random decision making, increasing task complexity does not worsen the decision making of seniors as a whole.

Next, we estimate probit and OLS models to better understand the determinants of optimal decision making (Table 3). We include task characteristics and demographic characteristics described above, as well as several additional determinants of cognition and risk. Following Dohmen et al. (2011) we asked subjects the percentage of $100,000 lottery winnings they would invest in an asset that is equally likely to double or halve over the next year as a way of measuring risk attitudes, and coded responses as above or below a median 40 percent investment. As an additional measure of risk, we asked subjects if they are users of tobacco (Viscusi and Hersch, 2001). We also surveyed subjects as to whether they regularly gamble in casinos or play lottery games. Since games of chance revolve around probabilities, regular players may have a better understanding of probabilities than non-players. In addition, we include two measures of problem solving acumen. As a measure of mathematical inclination, we asked subjects five arithmetic questions and include the number of right answers as "math count correct". To gauge cognitive inclination, we included the number of correct answers to the three-question cognitive reflection test (CRT) of Frederick (2005). The CRT questions have intuitive answers that are easily seen to be incorrect upon reflection.

The results of the regressions confirm the insights apparent in Table 2. Age has a highly significant negative effect on decision making. Attending college leads to a weak improvement in performance while graduate school attendance leads to a significant improvement ($p < 0.01$) by all measures. Members of the lower income group perform significantly better than the higher income group by all three measures.[3] People with more than three children performed better ($p < 0.1$ for all measures), perhaps reflecting a lifetime of experience navigating tough choices. Among the cognition and risk markers, the

[3] The notion of income for seniors may be subject to various interpretations (personal pre-retirement income, deceased spouse's income or benefits, household pre-retirement income, current personal income, etc.).

Table 3
Regressions for optimal choice and choice efficiency.

	Optimal option (probit)	Good option (in top 25%) (probit)	Efficiency (OLS)
Demographic characteristics			
Age	−0.043***	−0.037***	−0.019***
	(0.009)	(0.011)	(0.007)
College	0.260*	0.310	0.161
	(0.152)	(0.190)	(0.097)
Graduate	0.737***	0.864***	0.399***
	(0.180)	(0.222)	(0.121)
Male	0.146	−0.070	−0.051
	(0.151)	(0.192)	(0.105)
African-American	−0.349**	−0.368*	−0.070
	(0.171)	(0.211)	(0.131)
Income over $40,000	−0.527***	−0.549***	−0.248***
	(0.136)	(0.187)	(0.092)
Children > 3	0.290**	0.277*	0.155*
	(0.120)	(0.148)	(0.084)
Task characteristics			
8 options	−0.322***	0.613***	−0.010
	(0.100)	(0.102)	(0.051)
12 options	−0.389***	0.444***	0.002
	(0.108)	(0.097)	(0.053)
8 attributes	−0.217**	−0.046	−0.049
	(0.094)	(0.083)	(0.037)
12 attributes	−0.237***	−0.020	−0.023
	(0.084)	(0.070)	(0.037)
PDF 2	0.518***	0.521***	0.145***
	(0.096)	(0.121)	(0.040)
Cognition & risk			
Never used tobacco	0.086	0.053	−0.012
	(0.138)	(0.177)	(0.096)
Securities over 40%	−0.028	−0.090	−0.024
	(0.139)	(0.157)	(0.086)
Gambling	0.343**	0.454**	0.227**
	(0.150)	(0.184)	(0.110)
Math count correct	0.026	0.062	0.067
	(0.070)	(0.082)	(0.040)
CRT count correct	0.138	0.065	−0.002
	(0.147)	(0.155)	(0.061)
Constant	3.071***	2.524**	1.661***
	(0.761)	(0.996)	(0.592)
Observations	1155	1155	1155
Log likelihood	−665	−670	−1106

Robust standard errors clustered by subject in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

only clearly significant marker is experience with gambling and games of chance, where respondents performed better by all measures ($p < 0.05$).

Regarding task characteristics, additional options or attributes greatly reduce the chance of selecting the optimal option. Neither the number of options nor the number of attributes has a significant effect on efficiency or overall performance. However, increasing the number of options *increases* the chance of selecting a *Good* option. We next examine how the use of heuristics changes with age and task complexity.

4. Evolving heuristics

4.1. Effects of age

We examine three often-analyzed heuristics that are commonly used to make decisions among multi-attribute options: tallying, lexicographic, and undominated. Tallying discards probability information and simply sums the *number* of attributes for each option (Dawes, 1979). Lexicographic favors options that include the most probable attribute (Keeney and Raiffa, 1993). Undominated preserves options whose attributes are not strict subsets of other options (Montgomery, 1983). Additionally, we include payoff, the probability of receiving a payment, as an indicator for optimal choice, and model the importance of each decision-making paradigm using McFadden's (1974) conditional logit model.

Table 4
Age-specific heuristics estimated by conditional logit.

	60–67	68–74	75–79	80+	Pooled
Payoff	−0.698	1.288	−0.214	1.323	0.658
	(1.756)	(1.066)	(1.275)	(1.098)	(1.375)
Tallying	3.319***	3.905***	3.306**	1.918**	5.342***
	(1.116)	(0.975)	(1.371)	(0.910)	(1.056)
Lexicographic	2.781***	2.070***	0.365	0.838	2.885***
	(0.946)	(0.685)	(0.724)	(0.981)	(0.784)
Undominated	0.977***	0.647**	0.380*	0.084	1.050***
	(0.291)	(0.256)	(0.201)	(0.207)	(0.310)
Effect of age on ln(σ)					0.046***
					(0.014)
Log likelihood	−452	−417	−471	−494	−1866
Number of					
Options	2444	2428	2160	2196	9228
Decisions	305	304	270	276	1155
Subjects	17	17	15	16	65
Robust Lagrange multiplier test for heteroskedasticity:					768.7
p-Value					<0.001
Wald test statistic					10.0
p-Value					0.002
Estimated change in variance per year of age					+9.56%

Robust standard errors clustered by subject in parentheses. Pooled data is the heteroskedastic conditional logit with age = 60 as the reference category.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

An individual i is assumed to select the option o from a set C of available options that maximizes her utility: $u_{i,o} \geq u_{i,o'}, \quad \forall o' \in C$. The unobservable utility is given by $u_{i,o} = \alpha \boldsymbol{X}_o + \varepsilon_{i,o}$, , where $\boldsymbol{X}_o$ is a vector of option characteristics. If the error term follows an *i.i.d.* extreme value distribution, then the probability of selecting an option $o \in C$ is given by:

$$p_c(o) = \frac{e^{\alpha X_o/\sigma}}{\sum_{o' \in C} e^{\alpha X_{o'}/\sigma'}}$$

where σ is the measure of residual variation, proportional to standard deviation of the error term. We measure the four decision rules for each option on a 0–1 scale. In Fig. 1, option B would have a measure of 0.48 for payoff (the total probability of its two attributes), 0.5 for tallying (as it covers half of the available attributes), 0 for lexicographic (as it does not cover the most likely attribute) and 1 for undominated (as its attributes are not a strict subset of another option). Option C would have measures of 0.5 for payoffs, 0.5 for tallying, 0.25 for lexicographic (as one of four consecutive most likely attributes is covered), and 0 for undominated (as its attributes are a proper subset of option A).

In Table 4, we first estimate heuristics independently for each age quartile to ascertain whether the use of heuristics can account for the poorer performance by older seniors that we identified in the previous section. Subjects in the two youngest age quartiles (60–67 and 68–74) employ all three strategies: tallying, lexicographic, and undominated, with significance in declining order. Subjects in the third quartile rely on tallying and undominated, with both decreasing in magnitude and significance. Subjects in the oldest age quartile rely only on tallying. The youngest seniors show a breadth of heuristics more comparable to younger subjects in Besedeš et al. (2010), while the oldest group exhibits a reliance on fewer heuristics.

Overall, the magnitude of the parameters associated with the heuristics decline with age. However, one must be careful in drawing such conclusions as the coefficients estimated by the conditional logit may not be directly comparable across groups. As indicated above, the selection probability of a given option depends on α/σ, and therefore the reported coefficients confound the true effect of a heuristic with the (unobserved) measure of residual variation which can vary across groups (Amemiya, 1985). Thus, differences in the parameters across groups may be due to differences in σ or, alternately, parameters may appear equivalent across groups even though the true effect, α, varies (e.g., Allison, 1999).

As we are interested in both the heuristics different age groups may use and the degree of variance in decision-making across age groups, we employ the heteroskedastic conditional logit (Hensher et al., 1999; Hole, 2006) which estimates the change in residual variation across groups. Specifically, the residual variation is expressed as $\sigma_i = e^{\delta \boldsymbol{Z}_i}$ where δ is the parameter to be estimated and $\boldsymbol{Z}_i$ are the subject-specific characteristics (age measured as years above 60, in our case). As the last column of Table 4 indicates, variance increases significantly with age, at a rate of nearly 10 percent for each year of age.[4] As a result, an 80 year old subject, if using the same underlying heuristics, has a variance that is more than 6 times as large as a 60 year old subject. Thus, from the table as a whole, we can conclude that either older subjects rely on fewer and

[4] The estimated increase in variance is given by $(e^{0.046})^2 \cong 1.096$, where 0.046 is the estimate of the natural logarithm of the residual variation per year of age.

Table 5
Task-specific heuristics estimated by conditional logit.

	4 options	8 options	12 options	Pooled
Payoff	1.230	0.999	−0.933	0.378
	(1.063)	(1.204)	(0.858)	(0.673)
Tallying	2.724***	2.813***	4.908***	3.049***
	(0.627)	(0.658)	(1.238)	(0.575)
Lexicographic	1.223	1.496**	1.916***	1.594***
	(1.059)	(0.749)	(0.485)	(0.602)
Undominated	0.238	0.623**	0.201	0.518***
	(0.309)	(0.264)	(0.304)	(0.156)
Effect of number of options on ln(σ)				0.002
				(0.014)
Log likelihood	−438	−641	−788	−1901
Number of				
Options	1544	3088	4596	9228
Decisions	386	386	383	1155
Subjects	65	65	65	65
Robust Lagrange multiplier test for heteroskedasticity				0.02
p-Value				0.890
Wald test statistic				0.01
p-Value				0.911
Estimated change in variance per additional option				+0.32%

Robust standard errors clustered by subject in parentheses. Pooled data is the heteroskedastic conditional logit.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

fewer heuristics, and with less emphasis, as they age, or that there is a devolution to randomness as subjects age through increased variance of decision-making.

4.2. *Effects of number of options*

We next examine the choice overload hypothesis that people give up in the face of more options, devolving to random choice. Above we noted that the probability of selecting a *Good* option *increases* with the number of options. This is inconsistent with choice overload as the probability of selecting a *Good* option under random decision making is constant in our experiment. A more direct test estimates the heuristics used for each set of tasks with the same number of options, 4, 8, and 12. If the choice overload explanation is correct, we should see subjects devolving to random choice as the number of options increases, effectively relying on fewer heuristics as task complexity increases. In fact, we observe the opposite (Table 5). With four options, subjects rely solely on tallying, the only significant heuristic. With 8 options, while tallying remains the strongest heuristic, lexicographic and undominated are also significant ($p < 0.05$). With 12 options, in addition to tallying, lexicographic becomes highly significant ($p < 0.01$).

Reliance on different heuristics changes as the number of options increases. The tallying coefficient increases as the number of options increases, particularly from 8 to 12 options. The lexicographic coefficient also increases, though to a lesser extent. As argued in the previous section, drawing conclusions from this pattern of coefficients is problematic if there are differences in the unobserved residual variation. We again estimate the heteroskedastic conditional logit allowing residual variation to vary with the number of options and present the estimates in the last column in Table 5. Unlike our consideration of subjects by age, decisions do not exhibit significant differences in residual variation as the number of options increases.

Our finding of largely constant variance as the number of options increases should not be surprising as these are the same subjects making decisions in different tasks. This indicates that the consistency with which subjects apply heuristics does not depend on the complexity of the task they are facing. As there is no evidence of heteroskedasticity across tasks with different numbers of options, we can more comfortably compare parameters directly across groups (Allison, 1999). We find no evidence of choice overload, which would predict increasing variance of choice and reliance on fewer heuristics with task complexity. Rather than decreasing the number of heuristics as the number of options increases, our subjects actually begin to use additional heuristics, with the parameters for both tallying and lexicographic increasing with the number of options.

Given that tallying is preserved across all choices, we conjecture that other heuristics are used primarily to reduce the decision set to a manageable level. For example, one could concentrate only on options that cover the most likely attribute, or eliminate options that are clearly inferior to others in the choice set, thus applying aspects of lexicographic decision making or the elimination of dominated options. Hence, subjects may first be employing elimination strategies (Iyengar and Lepper, 2000; Timmermans, 1993), and then utilizing tallying to select among the remainder. For example, a subject facing 12 options may first use the lexicographic heuristic to remove all options that do not cover the most likely attribute from consideration, and then use tallying to select among the remainder. Similarly, a subject may first eliminate all dominated options. Previously, we noted that the likelihood of selecting the best option declines as more options are introduced.

Table 6
Frequency of selecting relatively bad options.

	Options	Frequency	Relative number of bad options
Tallying	4	14%	0.250
	8	8%	0.250
	12	7%	0.222
Lexicographic	4	39%	0.458
	8	20%	0.437
	12	30%	0.458
Dominated	4	23%	0.500
	8	23%	0.625
	12	26%	0.667

Table 7
Probit on selecting relatively bad options.

	Tallying	Lexicographic
8 options	−0.326***	−0.480***
	(0.117)	(0.093)
12 options	−0.401***	−0.231***
	(0.126)	(0.088)
Proportion of relatively bad options	1.914	3.448***
	(1.343)	(0.673)
Constant	−3.408***	−2.987***
	(0.914)	(0.704)
Observations	1155	1155
log likelihood	−337	−644

Robust standard errors clustered by subject in parentheses. The same demographic and cognition and risk variables as in Table 3 are included.
*$p < 0.1$, **$p < 0.05$.
*** $p < 0.01$.

Undominated and lexicographic strategies are quite likely to eliminate the worst options (Payne et al., 1993). Thus, the increased use of these heuristics would be expected to moderate the effects of task complexity and to result in a higher likelihood of selecting a good option.

In Table 6, we present evidence that is consistent with our conjecture. We examine the frequency with which subjects select relatively bad options according to the tallying, lexicographic, and undominated heuristics. For the tallying and lexicographic heuristics, we define "bad" options in a way that keeps the proportion of such options roughly constant across tasks with differing numbers of options. For tallying, bad options are defined as those that cover no more than 25 percent of attributes in tasks with 4 and 8 options, and no more than 42 percent of attributes in tasks with 12 options. This ensures that the proportion of bad tallying options is consistently near 25 percent. Yet, the frequency of selecting these bad options decreases as the total number of options increases. A similar pattern is observed for the other two heuristics. For lexicographic, bad options are defined as those that do not cover the top attribute. The frequency of selecting a bad lexicographic option is lower in 8- and 12-option tasks than in 4-option tasks. For undominated, the relative number of dominated options increases as the total number of options increases. However, the frequency with which dominated options are selected remains constant.

To examine the likelihood of selecting relatively bad options while controlling for the number of such options in a task, we estimate probit models. Our dependent variables are whether a subject selects a relatively bad tallying or lexicographic option (Table 7).[5] We include a control variable capturing the relative number of bad options in each task, as well as dummies for 8- and 12-option tasks. We also include (but do not present) controls for all demographic, cognition, and risk variables used in Table 3. The likelihood of selecting both bad tallying and bad lexicographic options decreases as the total number of options increases. While this is not direct evidence that subjects consciously eliminate bad options, it is consistent with a greater propensity to eliminate bad options per these heuristics as the number of options increases.

5. Conclusion

Research on decision-making performance of seniors has clear and urgent implications for the quality of life of this growing segment of the population. It is also highly relevant to the disposition of trillions of dollars in retirement savings plans and the large annual cost of healthcare for seniors. In each of these arenas, seniors are confronted with a wide array of choices, from the many available prescription drug plans to the numerous mutual funds offered with savings plans.

[5] Given our experimental design, the number of undominated options does not vary across tasks with the same number of option. This lack of variation prohibits estimation of such a model for the undominated heuristic.

Conventional wisdom holds that people simply throw up their hands and give up when faced with too much choice. To the contrary, we find evidence to suggest that seniors draw on additional heuristics to reduce the choice set to a manageable level and, in the process, are more likely to eliminate bad options than good ones. While increasing complexity does not as often lead to the optimal choice, it can lead to a good choice more often.

In a variety of settings, prior research has shown older subjects consistently make worse decisions compared with younger subjects. Here, we show important age effects within a senior citizen subject pool in terms of both the strategies used to approach complex decisions and the efficiency of subject's final choices. We find that performance abruptly declines in one's mid to late 70s. Specifically, seniors rely upon fewer and fewer heuristics as they age until choices essentially become random guesses. These results demonstrate the need to provide assistance to seniors who are making complex decisions. Clearly, this is an area in which more research is needed.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2011.07.016.

References

Allison, P., 1999. Comparing logit and probit coefficients across groups. Sociological Methods and Research 28 (2), 186–208.
Amemiya, T., 1985. Advanced Econometrics. Harvard University Press, Cambridge.
Besedeš, T., Deck, C., Sarangi, S., Shor, M., 2010. Age effects and heuristics in decision making. Review of Economics and Statistics, doi:10.1162/REST_a_00174.
Cabeza, R., 2002. Hemispheric asymmetry reduction in old adults: the HAROLD model. Psychology and Aging 17 (1), 85–100.
Cerella, J., 1985. Information processing rate in the elderly. Psychological Bulletin 98 (1), 67–83.
Cole, C.A., Balasubramanian, S.K., 1993. Age differences in consumers' search for information: public policy implications. Journal of Consumer Research 20 (6), 157–169.
Dawes, R.M., 1979. The robust beauty of improper linear models in decision making. American Psychologist 34 (7), 571–582.
Dohmen, T.J., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: measurement, determinants, and behavioral consequences. Journal of the European Economic Association 9 (3), 522–550.
Frederick, S., 2005. Cognitive reflection and decision making. Journal of Economic Perspectives 19 (4), 25–42.
Gilchrist, A.L., Cowan, N., Naveh-Benjamin, M., 2008. Working memory capacity for spoken sentences decreases with adult aging: recall of fewer but not smaller chunks in older adults. Memory 16 (7), 773–787.
Goldberg, M.E., 2009. Consumer decision making and aging: a commentary from a public policy marketing perspective. Journal of Consumer Psychology 19 (1), 28–34.
Hanoch, Y., Wood, S., Barnes, A., Liu, P.-J., Rice, T., 2011. Choosing the right medicare prescription drug plan: the effect of age, strategy selection and choice set size. Health Psychology, doi:10.1037/a0023951.
Hensher, D., Louviere, J., Swait, J., 1999. Combining sources of preference data. Journal of Econometrics 89 (1–2), 197–221.
Hole, A.R., 2006. Small-sample properties of tests for heteroscedasticity in the conditional logit model. Economics Bulletin 3 (18), 1–14.
Iyengar, S.S., Lepper, M.R., 2000. When choice is demotivating: can one desire too much of a good thing? Journal of Personality and Social Psychology 79 (6), 995–1006.
Johnson, M.M.S., 1993. Thinking about strategies during, before, and after making a decision. Psychology and Aging 8 (2), 231–241.
Keeney, R.L, Raiffa, H., 1993. Decisions with Multiple Objectives. Cambridge University Press, Cambridge, UK.
McFadden, D., 1974. Conditional logit analyses of qualitative choice behavior. In: Zarembka, P. (Ed.), Frontiers of Econometrics. Academic Press, New York, pp. 105–142.
Meyer, B.J., Russo, C., Talbot, A., 1995. Discourse comprehension and problem solving: decisions about treatment of breast cancer by women across the life span. Psychology and Aging 10 (1), 84–103.
Mittenberg, W., Seidenburg, M., O'Leary, D.S., DiGiulio, D.V., 1989. Changes in cerebral functioning associated with normal aging. Journal of Clinical and Experimental Neuropsychology 11 (6), 918–932.
Montgomery, H., 1983. Decision rules and the search for a dominance structure: toward a process model of decision making. In: Humphreys, P., Svenson, O., Vári, A. (Eds.), Analysing and Aiding Decision Processes. North-Holland, Amsterdam, pp. 343–369.
Payne, J.W., Bettman, J.R., Johnson, E.J., 1993. The Adaptive Decision Maker. Cambridge University Press, Cambridge, UK.
Scheibe, S., Blanchard-Fields, F., 2009. Effects of regulating emotions on cognitive performance: what is costly for young adults is not so costly for older adults. Psychology and Aging 24 (1), 217–223.
Schram, A., Sonnemans, J., 2011. How individuals choose health insurance: an experimental analysis. European Economic Review 55 (6), 799–819.
Schwartz, B., Ward, A., Monterosso, J., Lyubomirsky, S., White, K., Lehman, D.R., 2002. Maximizing versus satisficing: happiness is a matter of choice. Journal of Personality and Social Psychology 83 (5), 1178–1197.
Stern, P., Carstensen, L.L., 2000. The Aging Mind: Opportunities in Cognitive Aging. The National Academies Press, Washington, DC.
Tanius, B.E., Wood, S., Hanoch, Y., Rice, T., 2009. Aging and choice: applications to medicare. Part D. Judgment and Decision Making 4 (1), 92–101.
Timmermans, D., 1993. The impact of task complexity on information use in multi-attribute decision making. Journal of Behavioral Decision Making 6 (2), 95–111.
Viscusi, W.K., Hersch, J., 2001. Cigarette smokers as job risk takers. Review of Economics and Statistics 83 (2), 269–280.
Yoon, C., Cole, C.A., Lee, M.P., 2009. Consumer decision making and aging: current knowledge and future directions. Journal of Consumer Psychology 19 (1), 2–16.
Zimprich, D., Martin, M., 2002. Can longitudinal changes in processing speed explain longitudinal age changes in fluid intelligence? Psychology and Aging 17 (4), 690–695.
Zwahr, M.D, Park, D.C., Shifren, K., 1999. Judgments about estrogen replacement therapy: the role of age, cognitive abilities, and beliefs. Psychology and Aging 14 (2), 179–191.