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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 find a significant decline in performance with age due to reduced reliance on common heuristics among our oldest subjects. Subjects in their early sixties incorporate a wide array of heuristics, septuagenarians employ progressively fewer strategies, and subjects in their 80s make nearly random selections. 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.

JEL classification: C91, D03, I18
Keywords: experiments, decision making, choice overload, age effects, heuristics

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I. 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, Schram and Sonnemans 2011, Tanius et al. 2009). 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. Besedeš et al. (2010) also report that older subjects use suboptimal problem-solving approaches, or heuristics, when compared to younger subjects, leading to objectively worse choices with age.

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 with 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 paper and pencil experiments conducted at senior citizen activity centers in Baton Rouge, Louisiana. In-person experiments may provide a more representative sample of seniors than the online format of our related study (Besedeš et al. 2010). In both studies, subjects completed a series of choice tasks, where they were presented with several options and asked to select one. Each option contained several attributes, corresponding to a probability of receiving a payment, thus enabling us to evaluate objectively the relative quality of a subject's choices. The objective of this paper is twofold. First, we differentiate the effect 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.

Our data suggest that younger seniors 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 making decisions that are closer to random guessing than to optimal choices.

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 used to eliminate bad choices from consideration.

II. 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 in literal terms as colored balls, with the frequency distribution among colors given for each task. For example, Figure 1 illustrates a four option, four attribute choice task. Here, 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 and $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% chance of earning the larger payoff. This design (similar to Besedeš et al. 2010) ensures that all individuals have the same preferences over options, governed by the total probability of payment.

Figure 1: Sample choice task

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

Each subject was presented with a choice booklet and a survey booklet. Once subjects select an option in each task, one task is randomly selected to determine the subject's payment. Each subject is 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 free 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, followed by the 18 main tasks constituting a 3×3×2 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, akin to providing additional detail while not affecting 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.[2]

Three versions of the choice booklet varied the order of the 18 tasks. 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.

III. 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

[2] The survey instrument is available on request.

States			PDF1			PDF2			12 Options											
									8 Options											
			Number of States:			Number of States:			4 Options											
4	8	12	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	1		1				1	1		1		1
	Purple	Purple		6	3		21	5	1		1				1	1		1		1
		Orange			2			7	1		1				1	1		1		1
		Lt Blue			1			9	1		1				1	1		1		1
Pink	Pink	Pink	36	22	18	24	11	6	1				1	1			1	1	1	1
		Yellow			4			5	1				1	1			1	1	1	1
	Blue	Blue		14	14		13	13	1				1	1			1	1	1	1
White	White	White	45	11	11	26	8	8		1		1	1		1	1			1	1
	Brown	Brown		34	19		18	7		1		1	1		1	1			1	1
		Red			15			11		1		1	1		1	1			1	1
Green	Green	Green	11	8	8	22	13	13	1	1	1				1		1		1	
	Navy	Navy		3	3		9	9	1	1	1				1		1		1	
					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 1: Complete Experimental Design

of children (median split of 0-3 or >4). The first column presents the frequency with which subjects selected the optimal option.

		Optimal Option	Good Option (in Top 25%)	Efficiency	N
Overall		38%	58%	51%	65
By Demographic Characteristics					
Age	60-67	48%	66%	60%	17
	68-74	48%	68%	68%	17
	75-79	26%	46%	38%	15
	80+	28%	48%	35%	16
Education	At most high school	28%	47%	33%	22
	Some college or degree	39%	59%	53%	28
	Graduate education	51%	71%	72%	15
Sex	Female	37%	58%	52%	48
	Male	40%	55%	47%	17
Race	African-American	30%	50%	45%	11
	White and other	40%	59%	52%	54
Income	Less than 40k	39%	60%	54%	38
	Income more than 40k	36%	54%	47%	27
Children	Three or fewer	37%	57%	49%	39
	More than three	39%	58%	53%	26
By Task Characteristics					
Options	4	46%	46%	51%	65
	8	35%	66%	50%	65
	12	33%	61%	52%	65
Attributes	4	43%	58%	54%	65
	8	36%	56%	48%	65
	12	35%	58%	51%	65
PDFs	1	47%	66%	58%	65
	2	29%	49%	44%	65

Table 2: Choice frequency and efficiency

Subjects in the youngest two 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% chance of identifying the optimal option in the 4-option case, but only an 8% chance in the 12-option case. The second column of Table 1 examines the likelihood of selecting a *Good* option, which we define as an option in the top 25% 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% 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% with four options to 61% with 12 options. This again argues against choice overload.

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

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

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% efficiency, while older seniors are below 40%. 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.

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. (2010) 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% 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 casino 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 a series of 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

	Optimal Option (probit)	Good Option (in Top 25%) (probit)	Efficiency (OLS)
Demographic Characteristics			
Age	-0.044***	-0.039***	-0.019***
	(0.009)	(0.011)	(0.007)
College	0.261*	0.311*	0.158
	(0.150)	(0.182)	(0.097)
Graduate	0.742***	0.867***	0.394***
	(0.177)	(0.214)	(0.123)
Male	0.131	-0.092	-0.052
	(0.150)	(0.189)	(0.106)
African-American	-0.360**	-0.384*	-0.071
	(0.170)	(0.209)	(0.132)
Income over $40,000	-0.535***	-0.555***	-0.250***
	(0.136)	(0.185)	(0.092)
Children > 3	0.285**	0.269*	0.149*
	(0.119)	(0.144)	(0.084)
Task Characteristics			
8 options	-0.320***	0.605***	-0.009
	(0.097)	(0.101)	(0.052)
12 options	-0.382***	0.438***	0.006
	(0.107)	(0.095)	(0.052)
8 attributes	-0.221**	-0.062	-0.051
	(0.094)	(0.082)	(0.036)
12 attributes	-0.233***	-0.021	-0.026
	(0.084)	(0.069)	(0.037)
PDF 2	0.516***	0.512***	0.144***
	(0.095)	(0.117)	(0.040)
Cognition & Risk			
Never used tobacco	0.087	0.055	-0.017
	(0.138)	(0.174)	(0.095)
Securities over 40%	-0.025	-0.084	-0.020
	(0.138)	(0.152)	(0.086)
Gambling	0.363**	0.483***	0.232**
	(0.151)	(0.184)	(0.111)
Math count correct	0.022	0.054	0.066
	(0.069)	(0.080)	(0.040)
CRT count correct	0.136	0.061	-0.003
	(0.148)	(0.154)	(0.061)
Constant	2.623***	2.170**	1.528**
	(0.768)	(0.986)	(0.599)
Observations	1,170	1,170	1,155
log likelihood	-670.8	-679.2	-1103.0

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

Table 3: Regressions for optimal choice and choice efficiency

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 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.

IV. Evolving Heuristics

Individuals may use various strategies in solving complex problems. 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 the probability of payoff as an indicator for optimal choice, and model the importance of each decision-making paradigm using McFadden's (1974) conditional logit model. All four decision rules are measured on a 0-1 scale. In Figure 1, Option B would have a measure of 0.48 for payoffs (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

[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.).

most likely attributes is covered), and 0 for undominated (as its attributes are a proper subset of Option A).

Besedeš et al. (2010) found seniors, as a group, rely primarily on tallying while younger groups use a broader range of heuristics. In Table 4, we 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. The youngest age quartile (60-67) employs all three strategies: tallying, lexicographic, and undominated, with significance in declining order. Subjects in the next age quartile no longer use undominated, while subjects in the third quartile exhibit only tallying as statistically significant. For subjects in the oldest group, no heuristic is significant. Overall, the youngest seniors show a breadth of heuristics more comparable to younger subjects in Besedeš et al. (2010), while the oldest group exhibits a greater propensity for undirected choice, in line with the efficiency measures from Table 2 which indicated choices closer to random than optimal. The negative effect of age on decision making is due to subjects progressively discarding heuristics in decision making as they age, ultimately leading to decision making based more on guessing than any common criteria.

	60-67	68-74	75-79	80+
Payoff	-0.340	2.040	-0.055	0.945
	(1.763)	(1.123)	(1.285)	(0.907)
Tallying	3.622***	4.233***	3.467*	1.681
	(1.085)	(0.921)	(1.357)	(1.024)
Lexicographic	2.681**	1.806**	0.276	1.010
	(0.929)	(0.652)	(0.725)	(0.907)
Undominated	0.825*	0.324	0.289	0.292
	(0.334)	(0.240)	(0.214)	(0.227)
Log Likelihood	-452.5	-419.6	-471.7	-493.6
Observations	2444	2428	2160	2196

*** p<0.01, ** p<0.05, * p<0.1, robust standard errors clustered by subject in parentheses

Table 4: Age-specific heuristics estimated by conditional logit

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, undominated is also significant ($p<0.05$) and lexicographic is mildly significant ($p<0.1$). With 12 options, in addition to the always relied upon tallying, lexicographic becomes highly significant ($p<0.01$). Rather than decreasing the number of used heuristics as the number of options increases, as one would expect given the choice overload hypothesis, our subjects actually begin to use additional heuristics.

	4 options	8 options	12 options
Payoff	1.264	0.984	-0.687
	(1.066)	(1.084)	(0.866)
Tallying	2.681***	2.988***	5.185***
	(0.626)	(0.639)	(1.074)
Lexicographic	1.170	1.559*	1.794***
	(1.062)	(0.716)	(0.470)
Undominated	0.245	0.616**	0.100
	(0.310)	(0.193)	(0.222)
Log Likelihood	-437.8	-641.7	-789.6
Observations	1544	3088	4596

*** p<0.01, ** p<0.05, * p<0.1, robust standard errors clustered by subject in parentheses

Table 5: Task-specific heuristics estimated by conditional logit

Given that tallying is conserved across all choices, we hypothesize 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. Thus, subjects may first employ elimination strategies (Iyengar and Lepper 2000, Timmermans 1993), and then utilize tallying to select among the remainder. We noted that the likelihood of selecting the best option declines as more options are introduced. However, undominated and lexicographic strategies are quite likely to eliminate the worst options (Payne et al. 1993). The increased use of these heuristics moderates the effects of task complexity and results in a higher likelihood of selecting a good option.

V. 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.

Conventional wisdom holds that people simply throw up their hands and give up when faced with too much choice. To the contrary, we find 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. This is an area in which more research is needed.

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Appendix

Experiment Instructions

You are receiving $50 for participating in this experiment and completing a brief survey. The experiment consists of multiple tasks. Each task requires the completion of a response form on which you will make a choice from a set of alternatives appearing in a table such as the one below.

BALLS	**#**	**OPTIONS** Mark the letter option of your choice.					
		A	B	C	D	E	F
Red	10			✓	✓		✓
Orange	30		✓			✓	✓
Yellow	60	✓			✓	✓	

There will be a container of colored balls and one ball will be randomly drawn from the container at the end of the experiment. A volunteer from BREC will conduct the drawing in front of you. The column "BALLS" will list the colors of the balls in the container and the column "#" will list the number of balls of each color in the container. There will always be a total of 100 balls. Therefore, the chance that particular color will be drawn is the number of balls of that color /100. In this example, there is a 30/100 = 30% chance that an orange ball will be drawn.

Under the "OPTIONS" heading will be a set of letters. The letters correspond to options that you may choose. In the example on the previous page, one could choose option A, B, C, D, E, or F. Each option contains a series of checkmarks corresponding to the colored balls. For example, Option C has a checkmark for the color red only. Option D has checkmarks for both red and yellow.

For each task you will choose one and only one option by marking the letter of your choice with the provided marker. If you make a mistake or wish to change your response, please raise your hand and inform an experimenter. Marking multiple options will result in a loss of compensation.

You will make choices for 19 tasks. It is important that you make the choices in the order in which they are presented in the booklet. That is, you must complete the tasks in order and once you complete a task you cannot go back to it. Please do not go back to any previous pages.

After you have made all of your choices, please close your booklet. You may then complete the brief survey.

Once everyone has finished a volunteer from BREC will role a die to randomly determine which one task will be used to determine your payment. Even though you are making 19 decisions, only one will affect your payment.

The container will then be filled with the colored balls according to the “#” column for the randomly selected task and one ball will be randomly drawn from the container. If your chosen option for the selected task does not have a checkmark for the color of the ball drawn, you will lose $35 from the $50 you are receiving for participating in this study.

Below is an example. Suppose the following task was randomly selected and the person had chosen option F by marking it as shown below.

BALLS	**#**	**OPTIONS** **Place a round sticker on the letter option of your choice.**					
		A	B	C	D	E	
Red	10			✓	✓		✓
Orange	30		✓			✓	✓
Yellow	60	✓			✓	✓	

If an orange ball is drawn from the container, then this person as well as anybody else who chose options B, E, or F would be paid the $50 participation payment because options B, E, and F all contain a checkmark for orange. Anyone selecting options A, C, or D would receive the $50 participation payment minus $35 (for a total of $15).

After the drawing, a researcher will come to you to verify what you have earned. The researcher will give you a claim slip that you can use to collect your payment as you leave. When called, you will hand the claim slip to a researcher who will ask you to sign a receipt in exchange for your money. You will then drop your response booklet, survey, and marker in a large box. This process is designed to ensure that no one including the researchers can ever know the responses of any individual.

If you have any questions about the experiment, please ask now.

Otherwise, you may open your response booklet and begin. Keep in mind that you cannot go backwards through the booklet and should not answer the survey until you have completed the booklet.