The Relevance of Irrelevant Information

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Abstract

This paper experimentally investigates the effect of introducing unavailable alternatives and irrelevant information regarding the alternatives on the optimality of decisions in choice problems. We find that the presence of unavailable alternatives and irrelevant information generates suboptimal decisions with the interaction between the two amplifying this effect. Irrelevant information in any dimension increases the time costs of decisions. We also identify a "preference for simplicity" beyond the desire to make optimal decisions or minimize time spent on a decision problem.

JEL Codes: D03, D83, D91

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1 Introduction

In many decision problems, unavailable options along with irrelevant attributes are presented to decision makers. For example, a search on Amazon.com for televisions yields 1,239 different alternatives, 753 of which are unavailable at the time of search.[1] Additionally, these televisions are described by a great number of attributes: e.g. Refresh Rates, backlighting vs. no backlighting, size dimensions, availability of Wi-Fi connectivity, SMART vs non-SMART functions, number and types of inputs, etc. Many of these attributes may be irrelevant to some decision makers.

Consider some additional examples of unavailable alternatives:[2] In a restaurant menu, unavailable items may still be listed in the menu with a sold out note. A health insurance buyer will go over the insurance plans, some of which she is not qualified to purchase. A local event ticket website may list events that are sold-out. Also, consider some more examples of irrelevant attributes: Insurance coverage for care related to pregnancy may be presented to someone who could never get pregnant. The US Food and Drug Administration requires standardized nutrition label on food and beverage packages including fat, cholesterol, protein, and carbohydrate even when they are 0%, such as for a bottled water. Smartphones will list available service providers, even though this set will not vary across available smartphones.[3] From the perspective of classical rational choice theory, decision makers have *free disposal* of irrelevant information: they can costlessly ignore unavailable options and irrelevant attributes, and hence the presentation of such irrelevant information would not lead to different choices than those made when it is not presented. We experimentally demonstrate that the presentation set matters, providing evidence that the free disposal of irrelevant information is a non-trivial assumption in many contexts.

Our experiment is designed to test the effects of presenting irrelevant information in two dimensions. In a differentiated product setting, the decision problems presented to subjects vary according to a) the presentation of options in a set of alternatives that can never be chosen (here-

[1] Site accessed 02/02/2017.

[2] Note that in all of these examples, the firm/regulatory agency in question may have separate incentives for providing irrelevant information. These can be statutory (as in cases of regulated information provision), strategic (e.g. a firm may provide distracting irrelevant information to hide negative attributes), or because of dynamic considerations (e.g. an item may not be available currently, but the firm wants to signal the possibility that it is available in the future). We do not directly consider the firm's incentives in the current work, instead focusing on pure effect of irrelevant information on choice.

[3] An attribute that does not vary across available options may be *utility* relevant, but it is certainly not *decision* relevant information in that it does not meaningfully distinguish one good from another.

inafter referred to as unavailable options) and b) the presentation of attributes that have no value (i.e. that enter into a linear utility function with an attribute-level coefficient of zero; hereinafter referred to as irrelevant attributes). We find significant evidence that the presence of unavailable options and irrelevant attributes can increase the frequency of sub-optimal choice and that this effect is amplified with the interaction between the two.

Furthermore, motivated by the variation in online shopping websites allowing consumers to sort on the products based on the attributes they consider relevant, as well as allowing them to exclude the unavailable alternatives, we ask if individuals are willing to pay to reduce the amount of irrelevant information presented to them. We show that subjects are willing to pay significant positive amounts not to see unavailable alternatives or irrelevant information. Such a payment is mainly due to the reduction in mistakes and time costs caused by the presence of unavailable options and irrelevant attributes. Nevertheless, individuals may have a "preference for simplicity" in the presentation of information implying an additional cost, a cognitive cost of ignoring the irrelevant information. In order to identify such a cognitive cost, we analyze the willingness to pay (WTP) of the subjects who always chose optimally, who don't make additional mistakes, and who experience no additional time costs in the presence of unavailable options and irrelevant attributes. Our results indicate that even these subjects are willing to pay positive amounts to change the presentation set.

To our knowledge, unavailable alternatives have only been studied in the context of the decoy effect, which is the presentation of an alternative that increases the preference for a target alternative. Although in a typical experiment on decoys, the decoy alternative is available in the choice set, Soltani et al. (2012) showed that displaying an inferior good during an evaluation stage, but making it unavailable at the selection stage, also generates the decoy effect. Also, the phantom decoy alternatives that are superior to another target option, but unavailable at the time of choice, increase the preference for the inferior target option (see e.g. Farquhar and Pratkanis (1993)). There are several meaningful differences between our experiment and this literature on decoy goods, phantom or otherwise. First, our experiment involves objective, rather than subjective payoffs, eliminating a possible channel through which phantom alternatives should affect choice. Second, much of the discussion in Farquhar and Pratkanis (1993) and related work concerns the effect that a phantom good can have on choice *when it is not recognized as a phantom*. Clearly, if an unavailable option is mistakenly viewed as available, it is plausible that this may affect choice in a number of theoretical settings. However, we ask a different question, namely, can irrelevant information affect choice when it is objectively presented as irrelevant?

Our experiment also complements the experimental literature investigating the effects of *relevant* information on choice optimality. In particular, Caplin et al. (2011) find that additional (available) options and increased "complexity" (additional relevant attributes in our context) lead to increased mistake rates.[4] Also, Reutskaja et al. (2011) present evidence from an eye-tracking experiment that subjects are unable to optimize over an entire set (given a large enough alternative set), but can optimize quite well over a subset (see also Gabaix et al. (2006)). One contribution of our work herein is to show that a similar effect is present for adding unavailable alternatives and increasing the number of irrelevant attributes.

In limited consideration models, the DM creates a "consideration set" from the *available* set of alternatives and then chooses from the maximal element of the "consideration set" according to some rational preference relation (see e.g. Masatlioglu et al. (2012), Manzini and Mariotti (2007; 2012; 2014), and Lleras et al. (2017)). Also, according to the boundedly rational model that focuses on attributes, the salience theory of choice, certain *relevant* attributes may appear to be "more salient" to a DM than others, causing them to be overweighted in the decision-making process (see Bordalo et al. (2012), Bordalo et al. (2013), and Bordalo et al. (2016)). Some other models of search in multi-attribute settings are also based on *available* options and attributes.[5] Several of these models of choice allow for a "pruning" stage, where the DM eliminates from consideration unavailable options or options that are dominated according to some binary relation. Attention-based models with such a pruning stage include Kőszegi and Szeidl (2012); Manzini and Mariotti (2007; 2012). In each of these models, unavailable options should have no effect on choice.[6]

Our results highlight that the DM considers not only the alternative set and the relevant attributes but also the presentation set in which unavailable options and the irrelevant attributes are

[4]Oprea (2019) also looks at "complexity" of decision rules, though in a different context than what we consider herein.

[5]See Klabjan et al. (2014); Sanjurjo (2017); Richter (2017), for example.

[6]Several other models can be considered to have a "pruning" stage, though this element of the model is less explicit relative to the attention-based models mentioned here. For example, Bordalo et al. (2012; 2013; 2016) can be considered to treat irrelevant attributes as "pruned" in that they are de-facto treated with zero salience and, hence, ignored. Additionally, Kahneman and Tversky (1979) include an "editing" stage wherein lotteries are re-expressed by compressing payoff-equivalent states and therefore the lottery framing information of this form is "pruned." The latter model is less explicitly connected to our experiment, but is mentioned for posterity.

presented. Such an approach is taken in Guney et al. (2018). The presentation of a decision problem can be viewed as a "frame" as in Salant and Rubinstein (2008). However, if the DM chooses the best option when the presentation set is simple, but chooses a subotimal option by using a boundedly rational model, such as a model of satisficing as in Simon (1955), when the presentation set is more complex, such an extended choice function induces a choice correspondence that cannot be described as the maximization of a transitive, binary relation. We discuss this formally in Section 5.

The rest of the paper is organized as follows. Section 2 explains the design of the experiments in detail. Sections 3 and 4 present the results for our main experiments and control experiments, respectively. Section 5 discusses our results in light of extant theory and suggests a "presentation set" approach to modelling choice and Section 6 concludes.

2 Experimental Procedure

The experiments were run at the Experimental Economics Lab at the University of Maryland (EEL-UMD). All participants were undergraduate students at the University of Maryland. The data was collected in 14 sessions and there were two parts in each session. No subject participated in more than one session. Sessions lasted about 90 minutes each. The subjects answered forty decision problems in Part 1, and a subject's willingness to pay to eliminate unavailable options and irrelevant attributes were elicited in Part 2. In each session the subjects were asked to sign a consent form first and then they were given written experimental instructions (provided in Appendix A) which were also read to them by the experimenter. The instructions for Part 2 were given after Part 1 of the experiment was completed.

The experiment is programmed in z-Tree (Fischbacher, 2007). All amounts in the experiment were denominated in Experimental Currency Units (ECU). The final earnings of a subject was the sum of her payoffs in ten randomly selected decision problems (out of forty) in Part 1, her payoffs in two decision problems she answered in Part 2, the outcome of the Becker et al. (1964) (BDM) mechanism in Part 2, and the participation fee of \$7. The payoffs in the experiment were converted to US dollars at the conversion rate of 10 ECU = 1 USD. Cash payments were made at the conclusion of the experiment in private. The average payments were \$27.90 (including a \$7 participation fee).

Each decision problem in the experiment asked the subjects to choose from five available options and each option had five relevant attributes. Each attribute of an option was an integer from {1,2,..., 9} and it could be negative or positive. The value of an option for a subject was the sum of its attributes. The subjects knew that their payoff from a decision problem would be the value of their chosen option if that decision problem was selected for payment at the end of the experiment. Figure 1 provides an example of both an available option and an unavailable option presented to the subjects (see Appendix A for examples of the decision screen presented to subjects in each decision problem). Note that the header of each column indicates whether an attribute enters to the option value as a positive or negative integer (plus or minus sign). Whether a column should be added, subtracted, or ignored when calculating the value of an option was only indicated in this header row, so this information had to be continually referenced as the subject considered options at lower positions on the screen.[7] In some decision problems, some of the attributes did not enter the value of an option and those were indicated by zero at the header.[8] In Figure 1, there are ten attributes with a zero in the header and this means that the option had ten irrelevant attributes which did not affect the value of the option for the subjects. In a given decision problem, there were either five relevant attributes (each one with either positive or negative integer value from $\{1, 2, \ldots, 9\}$) or fifteen attributes where five of them were relevant and ten of them were irrelevant. The value of an option was the sum of its positive and negative attributes and it was a randomly generated positive number to guarantee that the subjects will not lose money by choosing an option.

Figure 1: Options with 5 Relevant and 10 Irrelevant Attributes

		+	+	**0**	**0**	**0**	+	**0**	**0**	**0**	**0**	+	**0**	**0**	**-**	**0**
☐	Option 1	three	four	three	one	seven	four	four	two	six	two	eight	five	two	six	one
	Option 2	one	eight	two	six	one	five	nine	two	six	two	eight	three	one	seven	nine

[7]Note that this design stands in contrast to Gabaix et al. (2006) and Caplin et al. (2011). In each of those experiments, the coefficient applied to an attribute appeared directly next to the attribute. To port that design directly to address our research question, we would then have to display zeros for irrelevant attributes as cells in the matrix. In our view, this limits the applicability to real-world scenarios in which we think that information may be irrelevant, even subjectively. We are interested in an environment where information is *displayed*, but not *valued*. Our current design addresses such an environment. Furthermore, by including coefficients in the column header only, we treat irrelevant attributes and unavailable options symmetrically, a necessary design component in order to interpret our findings with sufficient generalizability.

[8]Our design of varying irrelevant information in two dimensions will later be shown to create symmetric difficulty for subjects. Even though one may think that the perceptual operations required to solve a task are very different in these two dimensions (keeping track of payoffs horizontally and vertically), the impact of these two dimensions on optimality of choice turn out to be similar.

Regardless of the type of decision problem, the matrix of information presented to the subject took up the entire screen. This design was chosen to abstract away from possible confounds that lie in the *way* that information is presented. No matter which type of decision problem the subject faced, their eyes were forced to scan the entirety of the screen in order to fully process all relevant information. In this way we abstract away from the possibility that subjects are more capable of processing less (or more) visual space on a computer screen.

In each decision problem, the subjects needed to choose one of the five available options in 75 seconds.[9] In some decision problems they were presented fifteen options and told that only five of them were available to choose from. The other ten were shown on their screens but the subjects were not allowed to choose any of those. O_iA_j is the notation for a decision problem with i options and j attributes. The decision problems that were used in the experiment had $i, j \in \{5, 15\}$; in each case the effective numbers of options and attributes were five, i.e. if the number of options or attributes on a screen was fifteen, then ten of those were either unavailable options or irrelevant (zero) attributes.[10]. Each subject saw the same set of 40 decision problems, differing only in the order in which they were encountered.[11] The order of the decision problems were randomized at the session-individual level (i.e. Subject 1, for instance, in each session, saw the same order of decision problems; with 16 subjects per session, we therefore have 16 distinct decision problem orderings).

Once Part 1 of the experiment was completed, subjects received instructions for Part 2. The aim of Part 2 was to elicit subjects' willingness to pay to eliminate unavailable options or irrelevant attributes to estimate the cost of ignoring irrelevant information. A BDM mechanism was used to measure subjects willingness to pay to remove irrelevant information in one direction. Hence, we elicited the subjects' WTP in four different directions: moving from i) $O_{15}A_5 \rightarrow O_5A_5$, ii) $O_5A_{15} \rightarrow O_5A_5$, iii) $O_{15}A_{15} \rightarrow O_5A_{15}$, and iv) $O_{15}A_{15} \rightarrow O_{15}A_5$.[12] The distribution of selling prices used in the BDM procedure (and explained to subjects) was uniform from 0 to 15 ECU. These four BDM elicitation procedures were conducted across two treatments for Part 2 of our experiment: a "Low Noise" treatment and a "High Noise" treatment. Seven sessions were conducted

[9] Subjects earned a payoff of \$0 if they didn't make a choice within 75 seconds.

[10] We also conducted some control experiments for $i, j \in \{5, 8\}$ where we added three (rather than ten) unavailable options or irrelevant attributes to decision problems. Results for those experiments are in Section 4 and Appendices C.1 and C.2

[11] The complete set of decision problems is available as an online Appendix.

[12] Two additional sessions were conducted for robustness wherein we asked for WTP for $O_{15}A_{15} \rightarrow O_5A_5$. These results are explained in Section 4 and included in Appendix C.3.

for each treatment. In the Low Noise treatment, BDM procedures were run for (i) and (ii) - WTP was elicited for removal of options or attributes, *given that irrelevant information in the opposite dimension was not present.* In "high noise" treatments, BDM procedures were run for (iii) and (iv) - WTP was elicited for removal of options or attributes, *given that irrelevant information in the opposite dimension was present and cannot be eliminated.* Hence, we elicited the cost of ignoring 10 unavailable options and cost of ignoring 10 irrelevant attributes separately and in two different informational environments. Note that a given subject completed two BDM procedures, with roughly half of our subjects completing (i) and (ii) and half of them completing (iii) and (iv). We chose this between-subject design to eliminate a possible framing effect where a subject may have thought that she was expected to price the elimination of unavailable options or irrelevant alternatives differently depending on the amount of information in the other dimension. Table 1 summarizes the treatments of the experiment.

Table 1: Treatment Summary

Treatment	# of Sessions	# of Subjects	Part 1: Decisions	Part 2: BDM
Low Noise	7	112	40 Decisions	$O_{15}A_5 \rightarrow O_5A_5$ and $O_5A_{15} \rightarrow O_5A_5$
High Noise	7	110	40 Decisions	$O_{15}A_{15} \rightarrow O_5A_{15}$ and $O_{15}A_{15} \rightarrow O_{15}A_5$

Subjects completed Parts 1 and 2 without being provided any feedback on their performance in earlier decision problems similar to the experiments in related literature. First, we did not provide feedback after each decision problem in Part 1 in order to avoid any reference dependence or triggering new emotions such as regret. For example, a subject may work harder than she otherwise would if she knows that she would receive feedback on how suboptimal her decision was. Second, we do not provide aggregate feedback at the end of Part 1 to avoid unnecessary priming and to more closely approximate an analogous real-world setting. Direct feedback regarding mistake rates and/or time spent in each decision problem type may induce the subject to think that they should be willing to pay to eliminate irrelevant information, even if the subject does not intrinsically possess such a preference. We view the potential effect of feedback in this setting as analogous to an experimenter demand effect.

After the completion of Parts 1 and 2, the subjects answered a demographic questionnaire where they reported gender, age, college major, self-reported GPA, SAT, and ACT scores, and they were given the chance to explain their decisions in Part 2 of the experiment.

3 Experimental Results

Our main hypothesis is that unavailable options and irrelevant attributes cause cognitive overload for the decision makers and this leads to sub-optimal choice. In the following analysis, we say that a "mistake" has been made in an individual decision problem when the subject failed to select the highest valued available option presented within the time limit of 75 seconds. If no option was chosen, this is coded as a "timeout."

3.1 Part 1: Decision Task

In this section we present the results from Part 1 of the experiment. We begin with aggregate results and then re-investigate these results by controlling for decision problem characteristics and demographic controls.

3.1.1 Aggregate Results

Table 2 presents the mistake rate for each type of decision problem O_iA_j in the aggregate data for $i, j \in \{5, 15\}$, treating timeouts as mistakes, calculating the "mistake rate" for each treatment as the average of subject-level mistake rate. Note that the addition of unavailable options and irrelevant attributes alone does not generate significantly larger mistake rates relative to the benchmark O_5A_5 (p-values 0.584 and 0.653, respectively for decision problem types $O_{15}A_5$ and O_5A_{15}). However, conditional on the presence of either unavailable options or irrelevant attributes (in types $O_{15}A_5$ and O_5A_{15}), the addition of irrelevant information in the opposite dimension does increase mistake rates by about 50% (p-value 0.000 in each case). Thus, in the aggregate, the interaction between unavailable options and irrelevant attributes generates increased mistake rates. We believe that this is evidence that our design does not favor one type of irrelevant information over the other. If, for some reason, our design explicitly allowed for easier processing of either unavailable options or irrelevant attributes, we'd expect to see that mistake rates would respond to an increase in irrelevant information in only one dimension. This is clearly not the case. As such, we would expect our mistake rate results to be robust to permutations of our design, for example, where the matrix of displayed data was transposed. The results are qualitatively similar when we do not count timeouts as mistake. These results can be found in Table 15 in Appendix B.1. Additionally, when we instead measure welfare loss from sub-optimal choice by i) the rank of the chosen option among the available options or ii) normalized loss in monetary terms relative to optimal choice, our main result survives. These analyses can be found in Tables 25 and 26 in Appendix B.5.

Table 2: Mistake Rates: Timeouts as Mistakes

		O_5	O_{15}
A_5	Mean	0.213	0.218
	Std Error	0.013	0.013
	N	222	222
A_{15}	Mean	0.228	0.337
	Std Error	0.012	0.016
	N	222	222

$p = 0.000$ for $O_{15}A_5 \rightarrow O_{15}A_{15}$, $O_5A_{15} \rightarrow O_{15}A_{15}$, and $O_5A_5 \rightarrow O_{15}A_{15}$
$p > 0.100$ otherwise.

Note that when a subject finds a decision problem more challenging, she may react to this in two ways: (i) she may take more time to make decision and this may or may not lead to an optimal choice; (ii) she may run out of time and computer may record this as a sub-optimal choice. Even though the mistake rates in Table 2 do not change much when only the number of options is increased while the number of attributes are kept at 5 (from O_5A_5 to $O_{15}A_5$) and when only the number of attributes is increased while the number of options are kept at 5 (from O_5A_5 to O_5A_{15}), this does not necessarily mean that the subjects find the increased number of options or attributes in only one dimension not challenging. This increase in the difficulty of the decision problem may also appear as increased time required to submit a decision. Table 3 reports on the average time (in seconds) at which subjects submit a decision in each type of decision problem. Observations where the subject did not submit a decision in the allotted time were are excluded in Table 3 just as they were in Table 2. For results that treat timeouts as the maximum time allotted (i.e. $time = 75$)

and for the sub-sample where the subject chose the correct (optimal) option, see Tables 16 and 17 in Appendix B.1, respectively; results are not qualitatively different from those presented in Table 3.[13]

Note that adding irrelevant information in any dimension (i.e. unavailable options or irrelevant attributes) increases the time spent on each decision problem in Table 3. However, this difference is not statistically significant when moving from O_5A_5 to $O_{15}A_5$. Time costs increase much more substantially when irrelevant information in one dimension is already present. For example, the time spent increases by just over one second on average with the addition of unavailable options when there are no irrelevant attributes displayed (in the first row of Table 3), but increases by nearly 4 seconds when there are irrelevant attributes displayed (in the second row of Table 3). A similar effect is present for the addition of irrelevant attributes. Furthermore, from Table 3 we may surmise that irrelevant attributes increase time spent more than unavailable options: time spent increases more on average when moving vertically down in Table 3 than when we move horizontally across it. Both these interaction and asymmetry effects will be investigated further in the next subsection.

Table 3: Time: No Timeouts

		O_5	O_{15}
A_5	Mean	48.605	49.926
	Std Error	0.712	0.680
	N	222	222
A_{15}	Mean	52.935	56.365
	Std Error	0.780	0.810
	N	222	222

p = 0.00 for $O_5A_5 \to O_5A_{15}$, $O_{15}A_5 \to O_{15}A_{15}$, $O_5A_{15} \to O_{15}A_{15}$, $O_5A_5 \to O_{15}A_{15}$, and $O_{15}A_5 \to O_5A_{15}$
$p > 0.10$ for $O_5A_5 \to O_{15}A_5$

Finally, given that there is a time limit of 75 seconds for each decision problem, the increased

[13] An interested reader may wonder whether our central results are dependent on the specific time limit chosen in our design. First, note that in Table 17, the mean time taken to choose correctly is substantially less than the time limit of 75 seconds for each type of decision problem. We take this as evidence that our time limit was not meaningfully binding for a very large portion of our subject pool. Additionally, we conducted four pilot sessions under various design schemes, all without any time limit. Results, including mistake rates and time spent per problem, are qualitatively similar and are available upon request.

difficulty that could arise from the presentation of irrelevant information could also increase the rate at which timeouts occur in each type of decision problem. Recall that subjects earn zero in the case of a timeout and letting 75 seconds pass without a choice is worse than choosing randomly. Timeouts are not prevalent in our data: only 4.67% of decision problems resulted in a timeout. 60.31% of timeouts occurred within the first ten periods; 31.16% occurred in the first period. Further, note that our choice of a time threshold is somewhat arbitrary: we could have easily chosen to give subjects more (or less) time to complete each decision problem. As such, we ignore timeouts as a significant concern for the remainder of our analysis, conducting all tests conditional on experiencing no timeouts.[14]

From all of the above, we are left with the following main aggregate results: i) irrelevant attributes and unavailable options are *both* necessary to generate increased mistake rates, and ii) time costs are increased by irrelevant information displayed in either dimension. We summarize these findings in Result 1. In order to investigate each of these in more detail, we conduct regression analysis to control for individual-level heterogeneity and learning in the following subsection.

Result 1 *Decision makers cannot always freely dispose of irrelevant information.*

- *Unavailable options and irrelevant attributes can affect mistake rates. The interaction between the two amplifies this effect.*[15]
- *Both unavailable options and irrelevant attributes independently generate increased time costs.*

3.1.2 Decision Problem Characteristics and Demographic Controls

To further investigate the effects of irrelevant information on the mistake rate, we conduct logistic regressions controlling for learning, gender, and academic achievement effects. Table 4 reports regression results where the dependent variable is "Mistake" and the independent variables are varied in different models specified. "Mistake" is a binary variable with 1 corresponding to the subject failing to select the element with the maximal value in the set of (available) alternatives.

[14]There were four subjects who experienced timeouts in more than 20% of their decision problems. They are included in the sample upon which all analysis is conducted, but results are not qualitatively different if they are excluded.

[15]Additional results using alternative parameters that are discussed in Section 4 and Appendix C show that this finding is not driven solely by the increase in the amount in irrelevant information displayed; instead caused by the introduction of both unavailable options and irrelevant attributes).

It is equal to 0 otherwise. In all models, the independent variables are as follows: "Options" is a dummy variable indicating the presence of 10 additional unavailable options displayed (i.e. Options is equal to 1 for type $O_{15}A_5$ and $O_{15}A_{15}$ decision problems and it is 0 otherwise), "Attributes" is defined analogously for irrelevant attributes (i.e. Attributes = 1 for type O_5A_{15} and $O_{15}A_{15}$ decision problems), "Options * Attributes" is the interaction between the type dummies, "Female" is a dummy variable indicating whether the subject is female, "English" is a dummy variable indicating whether the subject's native language is English, "Economics/Business" is a dummy variable indicated whether the subject's major is in the University of Maryland Economics Department or Business School, and "Period" is the period in which the decision problem was presented. Reported coefficients are calculated marginal effects. Standard errors are clustered at the Subject level.

Cognitive Scores were calculated using a combination of responses on the Demographic Questionnaire. Responses for GPA, SAT, and ACT were normalized as in Cohen et al. (1999) and Filiz-Ozbay et al. (2016): Let j be the variable under consideration with $j \in \{\text{GPA, SAT, ACT}\}$, μ_i^j be the value of variable j for subject i, μ_{max}^j be the maximum value of j in the subject population, and μ_{min}^j be the minimum value of j in the subject population. Then let $\hat{\mu}_i^j$, the normalized value of variable j for subject i, be defined as follows:

$$\hat{\mu}_i^j = \frac{\mu_i^j - \mu_{min}^j}{\mu_{max}^j - \mu_{min}^j}$$

such that $\hat{\mu}_i^j$ can be interpreted as the measure of j for subject i, normalized by the distribution of j in the subject population. Some subjects were missing one or more measures for $j \in \{\text{GPA, SAT, ACT}\}$, since these measures were self-reported (and some subjects could not recall their scores on one or more of these measures). As such, the Cognitive Score for subject i was set to $\hat{\mu}_i^{GPA}$ if the subject reported a feasible GPA, $\hat{\mu}_i^{SAT}$ if a feasible GPA score was missing and the subject reported a feasible SAT score, and $\hat{\mu}_i^{ACT}$ if feasible GPA and SAT scores were both missing and the subject reported a feasible ACT score. GPA Scores were given precedent in the calculation of Cognitive Scores because most subjects could reliably report these while SAT Scores took precedent over ACT Scores because it is more common for University of Maryland, College Park undergraduates to have taken the SAT. Results based on using GPA only are presented in Appendix B.3 and are qualitatively similar.

In addition to the above specified independent variables, we include two more variables in all models: "Position" and "Positive". The variable "Position" is simply the position, from 1 to 15, of the optimal available option that is displayed. Previous work, including Caplin et al. (2011), has shown that subjects often search a list from top to bottom, implying that optimal options displayed lower-down on the list have a lower probability of being chosen due to the early termination of search. We thus include this variable as a control in each of our model specifications, its coefficient being significant and positive in all instances: subjects make more mistakes and spend more time when the optimal option is presented further down a list of alternatives. The variable "Positive" is the number of positive relevant attributes displayed in the decision problem, ranging from three to five.[16] There are potentially two reasons why "Positive" would matter in a given decision problem: i) a subject responds with increased effort in the presence of stronger incentives and ii) subjects find the task less difficult with fewer subtraction operations. The first comes from the fact that, given our data generation process, the expected value of the optimal available option is increasing in the number of positive attributes. Subjects may then work harder or stop search later in the presence of five positive attributes than in the presence of, say, three positive attributes. It also may be that subtraction operations are more difficult cognitively than addition operations such that the difficulty of the task is decreasing in the number of positive attributes. In Table 4, the coefficient on Positive is negative in all relevant model specifications: more addition operations decreases the incidence of mistakes. Clearly this is consistent with both increased effort provision and decreased cognitive difficulty of the task. However, the coefficient on Positive is also negative in all relevant models in Table 5, indicating that subjects spend less time in the presence of more addition operations. Combined, these results are consistent with addition operations being easier in terms of cognitive load.

Finally, any effects of irrelevant information that we may find could possibly be due simply to the increased *complexity* of the decision problem when irrelevant information is added, not due to the mere *presence* of irrelevant information. For example, adding unavailable options to a decision problem forces the DM to have to "skip" more visual information on the screen in order to evaluate

[16]Our data generation process gave equal weight to the possibility of having a positive or negative relevant attribute. However, we only used generated decision problems that i) had a unique optimal available option and ii) had all positive-valued available options. Thus, the range of the number of positive available options in the generated dataset is more restrictive than that which would be generated without these constraints.

an individual available option, since whether an attribute is positive or negative is displayed at the top of the screen. Similarly, irrelevant attributes force the DM to interrupt the evaluation process, visually "skip" a column of irrelevant information, and then continue with evaluation. Therefore, we define "Attribute Complexity" and "Option Complexity" as the number of "skips" required for full search/evaluation in the decision problem. For example, Option 1 in the example Figure 1 above, has a "Attribute Complexity" equal to 3 (since there are essentially three groups of irrelevant attributes encountered for full evaluation of the option). In the baseline O_5A_5 decision problems, both of these variables are set equal to 0. In the regressions reported in Tables 4 and 5, when "Options"("Attributes") is equal to 1, "Option Complexity" ("Attribute Complexity") varies between 2 and 5 in the realized data.[17]

The regressions in Table 4 are conducted on the sub-sample where the submission is made in under 75 seconds. As mentioned above, specifications that treat timeouts as mistakes or not are qualitatively similar (see Models 4 and 5 in Table 4). In Model 1, we replicate the aggregate result that can be seen in Table 2: unavailable options and irrelevant attributes increase the mistake rate when presented jointly. Having irrelevant information in both of these dimensions increases the mistake rate by up to 9.52 percentage points (in Model 4). Moreover, this effect is not due to the "complexity" of the decision problem in the presence of irrelevant information, as both Attribute Complexity and Option Complexity are insignificant in Model 4.

In order to investigate the heterogeneity in time responses to these different types of decisions problems, we present the results of several random-effect Tobit regression models in Table 5. Observations are censored below by 0 and above by 75 seconds.[18] In each model presented the dependent variable is Time (measured in seconds), defined as the time at which the subject submits her decision. As in previous model specifications, Models 1 - 4 are conducted on the sub-sample where the time of submission is less than 75 seconds (i.e. excluding timeouts and submissions in the last second). All variables are defined as previously mentioned. In Model 1, we present the simplest model incorporating the effects of the presence of irrelevant information on the time to reach a decision. We find results that are similar to those seen in Table 3: irrelevant information displayed in either dimension increases time costs considerably. Further, we confirm that there are

[17] We further explore alternative complexity measures for relevant subsamples of this dataset in Appendix B.4.

[18] To investigate the sensitivity of our results to this choice, we conduct further regressions using lower time thresholds. These can be found in Tables 18 and 19 of Appendix B.2.

Table 4: Mistake Rate Regressions

	(1) Mistake	(2) Mistake	(3) Mistake	(4) Mistake	(5) Mistake*
Options	0.009	0.009	-0.022*	-0.057**	-0.073**
	(0.011)	(0.011)	(0.013)	(0.028)	(0.029)
Attributes	-0.000	0.000	-0.006	-0.011	0.017
	(0.012)	(0.012)	(0.012)	(0.028)	(0.028)
Options * Attributes	0.087***	0.087***	0.093***	0.095***	0.100***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Period	0.000	0.000	0.000	0.000	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cognitive Score		-0.218***	-0.219***	-0.219***	-0.224***
		(0.063)	(0.063)	(0.063)	(0.063)
Female		0.077***	0.077***	0.077***	0.078***
		(0.021)	(0.021)	(0.021)	(0.021)
Economics/Business		-0.008	-0.008	-0.008	0.003
		(0.025)	(0.025)	(0.025)	(0.026)
English		-0.002	-0.002	-0.002	-0.013
		(0.022)	(0.022)	(0.022)	(0.023)
Position			0.004***	0.005***	0.006***
			(0.001)	(0.001)	(0.001)
Positive			-0.028***	-0.030***	-0.029***
			(0.008)	(0.008)	(0.008)
Attribute Complexity				0.001	-0.002
				(0.007)	(0.007)
Option Complexity				0.009	0.013*
				(0.007)	(0.007)
Observations	8555	8555	8555	8555	8880
Session FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Each Model: 222

*: Timeouts treated as mistakes

Marginal effects from logit regression specifications

Robust standard errors reported are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

interaction effects: that having both unavailable options and irrelevant attributes increases time spent by between 1.499 seconds (in Model 2) and 3.481 seconds (in Model 5) above the individual decision problem type effects. We also discover that irrelevant information has an asymmetric effect on time spent depending on the dimension: irrelevant attributes increase time costs more than unavailable options ($\beta_{Attributes} > \beta_{Options}$; $p-value = 0.000$). Finally, from Model 4 it can be seen that the effect of Options on time to make a decision stems from the increased complexity; Option Complexity is positive and significant in Model 4 while the coefficient on Options is insignificant.[19]

We summarize all of the aforementioned results in Result 2:

Result 2 *When controlling for subject-level heterogeneity and learning, we replicate the results found in Result 1. Namely, that subjects cannot always freely dispose of irrelevant information.*

3.2 Part 2: Willingness-To-Pay

Recall that the second part of the experiment elicited subjects WTP to eliminate unavailable options and irrelevant attributes in both "Low Noise" and "High Noise" environment. For reference, recall that the support of the BDM procedure used was $[0, 15]$ Experimental Currency Units (ECUs) with a uniform distribution. We have some observed variation in WTP data. By just looking at this CDF of submitted WTP amounts, Figure 2 reports that subjects are smoothly distributed in the support of the BDM range we provided. Such smooth distribution is also observed when we look at the WTP data for Low and High Noise environments separately.

Table 6 shows the average WTP, measured in ECUs, for each type of elimination. Table 6 can be read from left to right as "WTP to eliminate Attributes given that there are only 5 Options", "WTP to eliminate Options given that there are only 5 Attributes", etc. The first two columns belong to our "Low Noise" treatment and the last two belong to our "High Noise" treatment. Note that subjects participated in only one of these treatments; a given subject submitted her WTP for either columns 1 and 2 or columns 3 and 4. Thus, when making comparisons between WTP within a particular information treatment (Low or High), we match the data by subject. Let WTP to get rid of information be written as follows: $WTP(X|Y_n)$ where X is the dimension of information they

[19] Across all model specifications, we find some evidence of learning and subject-level heterogeneity, including gender, native language, and cognitive ability effects. However, our experiment was not explicitly designed to test for the effects of these demographic variables. As such, these results are included as statistical controls.

Table 5: Time Regressions

	(1) Time	(2) Time	(3) Time	(4) Time	(5) Time *	(6) Time **
Options	2.262***	2.265***	1.328***	-1.183	-1.109	-1.776*
	(0.350)	(0.349)	(0.441)	(0.889)	(0.965)	(0.950)
Attributes	5.114***	5.093***	4.808***	3.999***	5.079***	4.921***
	(0.426)	(0.426)	(0.432)	(0.926)	(1.084)	(0.931)
Options * Attributes	1.512***	1.499***	1.763***	1.872***	3.481***	2.126***
	(0.494)	(0.495)	(0.495)	(0.500)	(0.532)	(0.504)
Period	-0.264***	-0.264***	-0.264***	-0.264***	-0.206***	-0.300***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.020)	(0.028)
Cognitive Score		9.937**	9.927**	9.929**	6.523**	9.051**
		(4.142)	(4.142)	(4.142)	(3.276)	(4.251)
Female		-2.537*	-2.539*	-2.539*	-1.540	-2.378*
		(1.337)	(1.337)	(1.338)	(1.124)	(1.354)
Economics/Business		-2.302	-2.308	-2.310	-2.620*	-1.741
		(1.585)	(1.585)	(1.585)	(1.378)	(1.601)
English		-3.134**	-3.137**	-3.138**	-2.077	-3.451**
		(1.535)	(1.535)	(1.535)	(1.357)	(1.496)
Position			0.119***	0.151***	0.191***	0.181***
			(0.040)	(0.041)	(0.045)	(0.042)
Positive			-1.310***	-1.470***	-1.070***	-1.426***
			(0.262)	(0.267)	(0.275)	(0.280)
Attribute Complexity				0.227	-0.030	0.120
				(0.227)	(0.292)	(0.228)
Option Complexity				0.697***	0.584**	0.805***
				(0.207)	(0.232)	(0.222)
Observations	8555	8555	8555	8555	6668	8880
Session FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Each Model: 222

*: Conditional on Correct

**: Timeouts treated as Time = 75 seconds

Marginal effects reported from tobit regressions censored below by 0 and above by 75

Robust standard errors are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

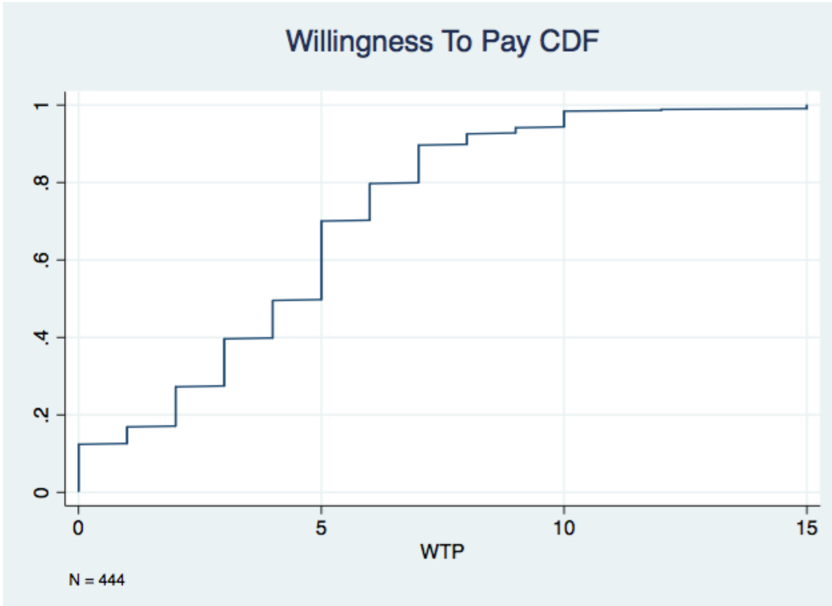

Figure 2: CDF of WTP

are paying to remove given Y-dimension information with n units. For example, $WTP(A|O_5)$ is the WTP to eliminate 10 irrelevant Attributes, given that five options are present (all of them available). WTP to reduce attributes is significantly higher than WTP to reduce options only in the low noise case. (p-value = 0.021 in Wilcoxon Signed-Rank Test with $H_0 : WTP(A \mid O_5) = WTP(O \mid A_5)$).

Tests of whether $WTP(A|O_5)$ is greater (less) than $WTP(A|O_{15})$ and whether $WTP(O|A_5)$ is greater (less) than $WTP(O|A_{15})$ were conducted un-matched as these were submitted independently by separate subjects. There is no significant difference between WTP to get rid of Attributes or Options by "Low Noise" or 'High Noise" treatment. Recall that eliminating irrelevant information in one dimension does not affect mistake rates significantly when there is no irrelevant information in the other dimension. However, eliminating irrelevant information in one dimension does affect the mistake rate when there is irrelevant information in both dimensions. Subjects do not seem to anticipate this effect on mistake rates when setting their WTP. Additionally, Table 7 reports the frequency of positive WTP for each treatment. The vast majority of our observations are strictly positive, with no statistical difference between treatments, either matched within subject or across Low Noise and High Noise treatments.

Average WTP for any case in Table 6 is between 4 and 5 ECU. One may question whether this amount is reasonable with respect to the mistakes subjects made in more difficult decision problems. If we compare the average amount of money subjects made in O_5A_5 versus O_5A_{15} and $O_{15}A_5$ and check whether the decrease in average earnings in decision problems with unavailable options or irrelevant attributes is less or more than the WTP in the corresponding decision problem, we may argue that subjects over- or underpaid to simplify their tasks. Such analysis gives us about a 1 - 2 ECU decrease in payoffs with more complicated problems and that is much lower than the observed WTP amounts. We will further explore one reason for such overpayment in Subsection 3.3: a "preference for simplicity."

Table 6: Willingness to Pay

	Low Noise		High Noise	
	$WTP(A\|O_5)$	$WTP(O\|A_5)$	$WTP(A\|O_{15})$	$WTP(O\|A_{15})$
Mean	4.473	4.071	4.473	4.373
Std Error	0.286	0.266	0.275	0.273
N	112	112	110	110

$p = 0.021$ for $H_0 : WTP(A|O_5) = WTP(O|A_5)$
$p > 0.100$ otherwise

Table 7: Frequency of Positive WTP

	Low Noise		High Noise	
	$WTP(A\|O_5)$	$WTP(O\|A_5)$	$WTP(A\|O_{15})$	$WTP(O\|A_{15})$
Mean	0.893	0.866	0.864	0.882
Std Error	0.029	0.032	0.033	0.031
N	112	112	110	110

$p > 0.100$ in all relevant comparisons

The regressions reported in Table 8 were conducted in order to understand the heterogeneity in the subjects willingness to pay in each of the four directions where irrelevant information could be removed. Table 8 displays results aggregated across the Low Noise and High Noise treatments. Note that in all these regressions, Attributes is a binary variable indicating whether the dependent variable is $WTP(A|O_n)$. When Attributes = 0, the dependent variable is $WTP(O|A_n)$.[20] The variable "High Noise" is a dummy variable used to indicate whether the observation is from a High Noise treatment. All interaction variables used in Table 8 are straightforward.[21]

First we ask if WTP to eliminate irrelevant information in either dimension is sensitive to

[20]For these regressions, answers submitted at *time* = 75 seconds are coded as mistakes to avoid collinearity of regressors.

[21]Table 22 of Appendix B.3 repeats the regressions reported in Table 8 by replacing the measure for Cognitive Score with self-reported GPA. The results are qualitatively the same.

measures of performance in Part 1 of the experiment, despite there being no feedback provided prior to Part 2. Models 1 - 3 are Tobit regression specifications with a lower limit of 0 and an upper limit of 15 (i.e. the support of the BDM mechanism used in Part 2 of the experiment). Note that in all models, Mistakes and Time are a count of the number of mistakes and the sum of time spent across all decision problems in the treatment under consideration for WTP. For example, if a subject in the low noise WTP treatment made 7 mistakes across the 10 O_5A_{15} decision problems and spent a total of 500 seconds across these same 10 decision problems, Mistakes would equal 7 and Time would equal 500 for the observation of $WTP(A \mid O_5)$ for this subject.

WTP increases with the incidence of mistakes: Mistakes is positive and significant in all models in Table 8. This is somewhat surprising, given that subjects were not provided feedback between Parts 1 and 2 of the experiment; it seems that subjects are aware of a general level of optimality of choice and are thus more willing to pay to eliminate irrelevant information if they make more mistakes in the corresponding decision problem type.

Additionally, we ask if these performance measures influence *whether* WTP is positive: it is possible that WTP itself is not sensitive to individual measures of performance, but that performance in one dimension can affect whether WTP is positive at all. Models 4 through 6 report coefficients from logistic regression specifications where the dependent variable is a binary variable indicating whether WTP is greater than 0. There is evidence that whether WTP is greater than zero is affected by Mistakes (see Models 4 - 6).

Notably, WTP is not sensitive to increased time spent on decision problems (see coefficient on Time in Models 1 - 6 in Table 8; Time is only marginally significnat in Model 2). Additionally, subjects appear to be more willing to pay to eliminate any irrelevant information in the High Noise treatments rather than the Low Noise treatments (see coefficients on High Noise in Models 1 and 2). This is true only at the intensive margin (i.e. in Models 1 - 2) and is at varying (and marginal) significance levels across these same models. Further note that in Table 6 we showed that WTP was higher for the elimination of Attributes than for the elimination of Options, though only in the Low Noise treatment. This result disappears in Table 8 when we have performance and demographic controls. We think that (lack of) feedback provided to subjects may prevent them from setting consistent WTP in Low Noise and High Noise treatments and between Attributes and Options. Further study on the role of feedback in such environments is necessary. We summarize these results in Result 3:

Table 8: WTP Regressions

	(1) WTP	(2) WTP	(3) WTP	(4) WTP > 0	(5) WTP > 0	(6) WTP > 0
Mistakes	0.413***	0.407***	0.329***	0.379***	0.333***	0.341**
	(0.102)	(0.104)	(0.118)	(0.124)	(0.121)	(0.156)
Time	0.003	0.003*	0.003	0.002	0.002	0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Attributes	0.191	0.189	0.312	0.022	0.010	0.205
	(0.156)	(0.155)	(0.276)	(0.159)	(0.158)	(0.301)
High Noise	2.296*	2.557**	1.961	0.793	0.729	1.185
	(1.200)	(1.216)	(2.416)	(1.401)	(1.505)	(2.589)
Female		-0.276	-0.245		0.473	0.467
		(0.440)	(0.433)		(0.487)	(0.475)
Cognitive Score		-0.992	-1.021		-1.355	-1.331
		(1.138)	(1.119)		(1.044)	(1.047)
High Noise * Mistakes			0.152			-0.015
			(0.199)			(0.228)
High Noise * Time			0.001			-0.000
			(0.004)			(0.004)
High Noise * Attributes			-0.237			-0.391
			(0.326)			(0.328)
Constant	0.394	1.076	1.278	-0.038	0.813	0.667
	(1.281)	(1.438)	(1.725)	(1.363)	(1.560)	(1.824)
Observations	444	444	444	386	386	386
Session FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
Number of Subjects in Baseline: 222
29 Subjects dropped from Models 4 - 6 because session FE perfectly predicts WTP > 0
Models 1 - 3: Tobit regression specifications with lower limit of 0 and upper limit of 15
Models 4-6: Logit regression specifications
Robust standard errors reported are clustered at the Subject level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Result 3 *WTP is heterogeneous and sensitive to a number of independent variables:*

- *WTP increases with the number of mistakes made in the relevant decision problem type*
- *Higher mistake rates increase the likelihood that WTP is strictly positive*

Notice that in Models 1 - 3 of Table 8, the constants are positive, though insignificant. For example, consider a subject for whom irrelevant information has no effect: they never make more mistakes when irrelevant information is present and they never spend more (or less) time. This subject may *still* be willing to pay some amount to eliminate this information. We'll call this a "preference for simplicity" - even in the absence of any effect of irrelevant information on choice, decision makers prefer to exclude it. We investigate this further by analyzing individual WTP for those subjects who experience no increase in mistake rates in the presence of irrelevant information in the following subsection.

3.3 A Preference For Simplicity

To more precisely estimate whether and to what extent such a preference for simplicity exists, we look at WTP for two categorizations of subjects for a given decision problem: i) those who experience no additional mistakes and ii) those who make no additional mistakes and incur no time costs associated with the presence of irrelevant information. Our interpretation of "making no additional mistakes" is straightforward: a subject is deemed to have made "no additional mistakes" in decision problems of type O_iA_j if her mistake rate in O_iA_j was weakly less than her mistake rate in O_iA_{j-10} for $j = 15$ (or $O_{i-10}A_j$, for $i = 15$). In other words, a subject is counted in the first row of Tables 9 and 10 if she indeed made no additional mistakes as a result of irrelevant information in the relevant dimension. For example, a subject in the High Noise treatment who made 2 mistakes in $O_{15}A_5$ and 1 mistake in $O_{15}A_{15}$ will be considered to have made "no additional mistakes" in $O_{15}A_{15}$ because her mistakes didn't increase with the addition of irrelevant attributes. In all of the analysis in this section, Timeouts were treated as Mistakes, but results are robust to the exclusion of Timeouts.

We additionally consider subjects who make no additional mistakes *and* incur no additional time costs. A subject is deemed to have incurred no time costs if the difference in the amount of time that she spends in decision problems of type O_iA_j is not significantly different from the amount of time she spends in decision problems of type O_iA_{j-10} for $j = 15$ (or $O_{i-10}A_j$, for $i = 15$). In other words, a subject is counted in the second row of Tables 9 and 10 if she made "no additional mistakes" as per the interpretation presented in the previous paragraph *and* she did not spend significantly more time on a type of decision problem as a result of irrelevant information.[22]

[22]In all relevant analysis, "No Additional Mistakes" and "No Additional Mistakes or Time Costs" are defined at the subject-O_iA_j decision problem type level, independent of behavior in other decision problem types. As such, a subject could be considered to have made "No Additional Mistakes" in some decision problems, but not others, and

We present the summary statistics of WTP in Table 9 and the frequency of positive WTP amount in Table 10. The mean WTP and fraction of WTP greater than zero is positive and significant at the 5% level in each case. Additionally, a comparison between Tables 9 - 10 and Tables 6 - 7 reveals that the mean WTP and frequency of positive WTP closely matches that of the overall sample. In Tables 9 and 10, we can reject a null hypothesis $H_0 : \mu_{\text{No Additional Mistakes (or Time Costs)}} = \mu_{\text{Additional Mistakes (or Time Costs)}}$ in a Mann-Whitney test in each of the 16 instances. For example, in Table 9 the mean $WTP(A \mid O_5)$ of 4.226 ECU for the 62 subjects who make No Additional Mistakes is not significantly different than the mean $WTP(A \mid O_5)$ for the remaining 50 subjects in the Low Noise treatment at any standard α level. Note that in no instance in Tables 9 and 10 is there a significant difference; mean WTP and frequency of positive WTP, overall, does not depend on whether or not the subject made No Additional Mistakes (or Time Costs).

Additionally, let $y(I|J_k) = 1\{WTP(I|J_k) > 0\}$ indicate whether WTP to eliminate irrelevant information in the Ith dimension, given that there are k units of information in the Jth dimension, is positive. A Kolmogorov-Smirnov test of equality of distributions fails to reject the null $H_0 : F(y_{\text{additional mistakes}}(I|J_k)) = F(y_{\text{no additional mistakes}}(I|J_k))$ for each (I, J_k). Such tests also fail to reject the analogous null for WTP levels themselves ($H_0 : F(WTP_{\text{additional mistakes}}(I|J_k)) = F(WTP_{\text{no additional mistakes}}(I|J_k))$).

All of this taken together provides evidence that even subjects for whom irrelevant information neither affects the optimality of choice nor increases time spent on a decision problem prefer not to see such irrelevant information; there exists a preference for simplicity of the informational environment, even when irrelevant information has no effect on choice. Moreover, a brief look at responses to the open-ended question in our questionnaire reveals similar reasoning for some of our subjects. A subject who made no mistakes responded that "I chose [positive WTP amounts] to relax my eyes a little bit." Another responded that "either one [of eliminating irrelevant attributes or unavailable options] wouldn't be too helpful, but they still kind of help, so I put a low number and if I got it I got it, if I didn't, oh well." One possible explanation for this preference for simplicity may be that there is an additional dimension of cognitive effort spent on these decision problems that is not fully captured by mistake rates or time costs. Said another subject, "[...] unavailable

may appear in some cells of Tables 9 and 10, but not all. These measures do not require any joint conditions over multiple decision problem types for a given subject.

options and attributes are distracting and cause me to *work harder* and longer when trying to calculate from options and attributes that are actually available. Therefore, I would be willing to pay ECU to get rid of them on the screen in order to work more efficiently and effectively" (emphasis added). To our knowledge, ours is the first study to identify such a preference, and this is the "cost of ignoring" in its purest form: there is a preference-based psychological consequence to having to ignore irrelevant information that is not captured by standard measures of the effect of irrelevant information on choice.

Table 9: WTP: No Additional Mistakes

	Low Noise		High Noise	
	$WTP(A\|O_5)$	$WTP(O\|A_5)$	$WTP(A\|O_{15})$	$WTP(O\|A_{15})$
No Additional Mistakes	4.226	4.000	3.930	4.133
	(.360)	(.324)	(.389)	(.387)
	62	68	43	45
No Additional Mistakes or Time Costs	4.130	4.031	4.192	4.146
	(.388)	(.338)	(.517)	(.396)
	54	65	26	41

Std. Errors in Parentheses
Sample mean > 0 at the $\alpha = 0.05$ level in each instance
Mann-Whitney $p > 0.1$ for $H_0 : \mu_{\text{No Additional Mistakes (or Time Costs)}} = \mu_{\text{Mistakes (or Time Costs)}}$ in each instance
Timeouts treated as Mistakes

Table 10: Frequency of Positive WTP: No Additional Mistakes

	Low Noise		High Noise	
	$WTP(A\|O_5)$	$WTP(O\|A_5)$	$WTP(A\|O_{15})$	$WTP(O\|A_{15})$
No Additional Mistakes	.919	.868	.837	.844
	(.035)	(.041)	(.057)	(.055)
	62	68	43	45
No Additional Mistakes or Time Costs	.907	.862	.885	.854
	(.040)	(.043)	(.064)	(.056)
	54	65	26	41

Std. Errors in Parentheses
Sample mean > 0 at the $\alpha = 0.05$ level in each instance
Mann-Whitney $p > 0.1$ for $H_0 : \mu_{\text{No Additional Mistakes (or Time Costs)}} = \mu_{\text{Mistakes (or Time Costs)}}$ in each instance
Timeouts treated as Mistakes

We summarize these results in Result 4:

Result 4 *There is a cost of ignoring irrelevant information that is not measured by mistake rates or time costs: subjects are willing to pay some amount not to see irrelevant information, even when* *irrelevant information does not affect choice.*

- *When measured in an analysis of WTP for subjects who make no additional mistakes in response to irrelevant information, this cost is positive.*
- *When measured in an analysis of WTP for subjects who make no additional mistakes in response to irrelevant information* and *spend no additional time in response to irrelevant information, this cost is again positive.*

4 Robustness Checks

In order to investigate to what extent our results are sensitive to the design specification used for these tasks, we conducted six additional sessions under alternative designs. Four of these sessions were conducted with alternative designs regarding Part 1 decision tasks and two of these sessions were conducted with alternative designs regarding the Part 2 willingness-to-pay tasks. These sessions are summarized in Table 11:

Table 11: Robustness Treatment Summary

Treatment	# of Sessions	# of Subjects	Part 1: Decisions	Part 2: BDM
8x8: Low Noise	2	32	40 Decisions	$O_8A_5 \rightarrow O_5A_5$ and $O_5A_8 \rightarrow O_5A_5$
8x8: High Noise	2	30	40 Decisions	$O_8A_8 \rightarrow O_5A_8$ and $O_8A_8 \rightarrow O_8A_5$
Alt-High Noise	2	30	40 Decisions	$O_{15}A_{15} \rightarrow O_5A_5$

In the treatments designated as "8x8" in the above table, decision tasks included a maximum of three unavailable options and three irrelevant attributes relative to the baseline in order to explore the effects of changing the parameter space on our main results. This resulted in decision task treatments O_5A_5, O_5A_8, O_8A_5, and O_8A_8. In the treatment named "Alt-High Noise", the decision tasks presented in Part 1 were the same as for the main treatments (i.e. O_5A_5, O_5A_{15}, $O_{15}A_5$, and

$O_{15}A_{15}$) . However, in Part 2, subjects were asked a single WTP question eliciting WTP to move from $O_{15}A_{15}$ to O_5A_5.

All relevant results are presented in Appendix C. In this section, we will highlight several important results that further illuminate the main contributions of this paper.

4.1 Further Investigation of the Mistake Rate Function

In Subsection 3.1, we argue that our results indicate that mistake rates are not affected by unavailable options and irrelevant attributes *linearly*; the presence of both unavailable options and irrelevant attributes simultaneously amplifies the effect of irrelevant information on mistake rates in our main experimental task. However, an apt reader may notice that with five available options each with five relevant attributes in each treatment, our main design leads to the following counts of irrelevant cells of information displayed to subjects as described by Table 12.

Treatment	Irrelevant Cells
O_5A_5	0
O_5A_{15}	50
$O_{15}A_5$	50
$O_{15}A_{15}$	200

Table 12: Treatments and Irrelevant Information

So since we find higher mistake rates in treatment $O_{15}A_{15}$ only, this could be the result of either a) interaction between the two types of irrelevant information subjects handled or b) the presence of an additional 150 irrelevant cells relative to treatments O_5A_{15} and $O_{15}A_5$. Using the alternative 8x8 design, we can more precisely investigate the effect of the "size" of the irrelevant information set on mistake rates. The 8x8 design leads to the counts of irrelevant cells of information as described by Table 13. Note that the O_8A_8 case in this experiment has fewer irrelevant cells than either $O_{15}A_5$ or O_5A_{15} of the main experiments. If mistake rates in treatment O_8A_8 are higher than in treatment O_5A_5 in this new dataset and treatments $O_{15}A_5$ and O_5A_{15} in the main dataset, we can thus conclude that this is the result of some non-linearities in the mistake rate function and not simply the size of the set of irrelevant information.[23]

[23] We would, however, like to caution the reader against interpreting these results as evidence that unavailable options and irrelevant attributes can *never* affect welfare for a DM. While this is mostly true in our experimental dataset, no single experiment (or set of experiments) can fully explore the parameter space of such decision problem such that we can precisely estimate the full specification of the mistake rate function. Our results simply indicate that

Treatment	Irrelevant Cells
O_5A_5	0
O_5A_8	15
O_8A_5	15
O_8A_8	39

Table 13: Robustness Treatments and Irrelevant Information

Table 27 in Appendix C.1 reports mistake rates across all decision problem types in the 8x8 treatments. The main messages of Tables 27 and 2 (for the main dataset) are similar: the interaction between unavailable options and irrelevant attributes are generates more suboptimal choice. Hence, we replicate our main finding on mistake rates with this additional dataset. Moreover, treatment O_8A_8 with 39 irrelevant cells displayed to subjects, has a mistake rate of 24.2%, which is higher than the mistake rates of both O_5A_{15} and $O_{15}A_5$ in the main dataset.[24] The results in Table 27 are robust to the exclusion of timeouts, reported in Table 28. Taken together, these additional analyses reveal that the central result contained in this work is indeed due to the presence of *both* unavailable options and irrelevant attributes, not simply due to the sheer amount of irrelevant information displayed.

Additionally, Appendix C.1 reports average Time spent in decision problems in the 8x8 treatments in Tables 29 through 31. Similar to our main dataset, Time spent in the 8x8 treatments increases in the presence of any irrelevant information, but more so for the addition of irrelevant attributes. Table 32 reports the incidence of Timeouts for the 8x8 treatments. Overall, timeouts occur in less than 3% of all observations in the 8x8 treatments, with the lowest incidence in decision problem type O_5A_5, similar to the main dataset.

4.2 Additional Willingness-to-Pay

The WTP results collected for the 8x8 treatments are similar to our results for WTP in the main experiments, where we observe positive WTP to eliminate irrelevant information (see Tables 33 and 34 in Appendix C.2). One thing worth noting here is that the average WTP is much lower in

there is sufficient evidence that, within the confines of our experimental design, the interaction between unavailable options and irrelevant attributes indeed matters.

[24]We also view mistake rates in the treatments used for robustness as lower bounds on true mistake rates. The mistake rate for the baseline treatment of this dataset was 16.8%, lower than the baseline mistake rate of 21.3% for the main dataset. This difference could be due to relative overall easiness of the robustness experiments with a maximum of O_8A_8 difficulty rather than $O_{15}A_{15}$ of the main experiments.

control experiments (Table 33 vs 6) and that subjects less frequently submit positive WTP amounts in control experiments than main experiments (Table 34 vs Table 7). This indicates that subjects perceived O_8A_8 as easier than $O_{15}A_{15}$ and hence they valued the elimination of unavailable options and irrelevant attributes much higher when they eliminate 10 rows or columns in a decision problem than when they eliminate 3 of the same.

As previously mentioned, we've shown that *both* unavailable options and irrelevant attributes are necessary to generate an increase in the mistake rate, with mistake rates in treatment $O_{15}A_{15}$ being significantly higher than in the baseline. We've also shown that WTP to eliminate irrelevant information is sensitive to individual mistake rates, even though subjects are not provided with feedback regarding their performance in Part 1 of the experiment prior to submitting their WTP.

To bridge these two results, we conducted an additional two sessions where Part 2 of the experiment was altered to only ask a single WTP question, with subjects submitting their WTP to move from $O_{15}A_{15}$ to O_5A_5. Our central hypothesis is that, because mistake rates are higher *only* in $O_{15}A_{15}$, WTP for $O_{15}A_{15}$ to O_5A_5 should be significantly higher than any other WTP measure. If we had asked, say, three WTP measures ($O_{15}A_{15} \to O_5A_{15}$, $O_{15}A_{15} \to O_{15}A_5$, and $O_{15}A_{15} \to O_5A_5$) in these sessions, the subject may be primed to internally rank these three WTPs with $O_{15}A_{15} \to O_5A_5$ as the "most valuable" simply due to the relatively large number of irrelevant cells eliminated. To avoid this priming, we ask for WTP for $O_{15}A_{15} \to O_5A_5$ alone.

We find results consistent with our hypothesis, as indicated in Tables 35 and 36 in Appendix C.3. Mean WTP for $O_{15}A_{15} \to O_5A_5$ is 5.452 ECU, higher than any other WTP measure previously elicited in the main dataset. Moreover, approximately 84% of subjects submitted a positive WTP for $O_{15}A_{15} \to O_5A_5$, very similar to the frequency of positive WTP reported in Table 7. Hence, subjects report positive WTP for $O_{15}A_{15} \to O_5A_5$ with the same frequency as for the observations in our main experiment, but they are willing to pay higher amounts. These results provide more credence to the notion that WTP to eliminate irrelevant information closely tracks performance in Part 1, even absent any feedback.

5 Discussion

From the above analysis we've shown that irrelevant information can increase the frequency of sub-optimal choice. This has implications for how we model both rational choice under constraints on attention and boundedly rational choice. We can reject purely random choice in each treatment: note that mistake rates in each treatment would be equal to 80% (since one of the five available options will always be optimal) if subjects choose randomly, giving each option an equal chance of being chosen. We can reject a null hypothesis that mistake rates are equal to 80% in each treatment ($p < 0.000$ in each). Likewise, we can reject fully rational choice (under no attention constraints) at the $\alpha = 0.001$ level.

Given that our results are consistent with neither random choice nor fully rational choice, it remains to be seen whether a behavioral model that allows for sub-optimal choice is consistent with our data. As mentioned in Section 1, models that allow for sub-optimal choice focus on *available* options and *relevant* attributes. In limited consideration based models of choice (see e.g. Masatlioglu et al. (2012), Manzini and Mariotti (2007; 2012; 2014), and Lleras et al. (2017)), the decision-maker first creates a "consideration set" from the set of *available* options. If the optimal option in the set of available options does not make it into the consideration set, it will not be chosen and choice will be sub-optimal. Similarly in models of satisficing and search (e.g. Caplin et al. (2011)), the decision-maker searches through the list of *available* options, leaving the potential to fail to consider the optimal option displayed. In models of rational inattention (see e.g. Sims (2003; 2006); Matejka and McKay (2014); Caplin and Dean (2015)), the decision-maker acquires information at some cost through a rational attention allocation process. In such a framework, the agent would optimally pay no attention to irrelevant information (i.e. unavailable options or irrelevant attributes). Similarly, the salience-based model of Bordalo et al. (2012; 2013; 2016) is based on *relevant* attributes only. In this model, attributes of a given option are weighted based on their distance from the mean value of that attribute across all goods that are available. Trivially, irrelevant attributes in such a model would have equal (zero) salience and would thusly be ignored.

To rectify our results with the extant body of literature, one would have to extend these models to incorporate dependence on *presented*, rather than *relevant*, information. The cost of acquiring information in a rational inattention framework, for example, could be modeled as dependent on the amount of irrelevant information displayed. Such an approach would also complement recent experimental results in Dean and Neligh (2017) that suggest that the Shannon mutual information model of rational inattention is too restrictive to allow for "perceptual difficulty" of ascertaining the state. Our results could be viewed through a similar lens: it is more difficult to perceive which option is optimal in the presence of irrelevant information, even though the state-space is payoff equivalent to the decision-problem without irrelevant information. In models of search or satisficing, one would have to assume that the decision-maker either a) has a cost-of-search parameter that depends on the presence of irrelevant information or b) searches through unavailable options mistakenly with some probability.

In this spirit, we propose the concept of a "presentation set" to be incorporated in more general choice theoretic models. A decision problem in such an approach would be defined as a (S, P)-tuple, with S and P as subsets of the grand set of alternatives such that $S \subseteq P$. While S is the set of available options displayed to the consumer, a (weakly) larger set P is *presented* to the consumer, with $s \in P \setminus S$ interpreted as unavailable options. An attribute-dependent modification of this approach is straightforward. Our results suggest that choices depend on P as well as S.

Such an approach is related to the work of both Guney et al. (2018) and Salant and Rubinstein (2008). In the former work, the DM chooses an "aspiration" that lies in the set of presented alternatives, but not necessarily in the choice set, which then affects the optimization process of the DM on the choice domain. Thus an irrelevant and unavailable alternative may affect choice. Our experiment abstracts away from aspiration-based choice in that there is no meaningful incentive for a subject to inspect the unavailable options and use them as a sort of utility reference point. In Salant and Rubinstein (2008), choice is affected by a "frame" which they define as including "observable information that is irrelevant in the rational assessment of the alternatives, but nonetheless affects choice." Since a "frame" is anything other than relevant information to the decision problem that can affect choice, the "presentation set" can be interpreted as a "frame". Nevertheless, this "presentation set" may trigger the DM to use a different choice procedure.

Consider the following example: a DM always optimizes (i.e. considers all options and chooses the best one) when the presentation set is equal to the set of available goods, but uses Simon's satisficing criteria for more complicated presentation sets. Further, suppose there are three available options, x, y, and z such that $U(x) > U(y) > U(z)$ for some utility function U and that $U(z) \geq \tau$, for some satisficing level of utility τ. Thus, if the DM is optimizing, she will choose x, but the DM will choose the first available option considered if following a satisficing criteria. Assume that there are two frames/presentation sets: f_1 where there is no additional information displayed other than the available goods and f_2 where x, y, and z are displayed along with unavailable goods.

Under f_1, the DM will always choose the U-maximal option, since the DM can optimize under simple frames/presentation sets. However, under f_2, the consumer will choose the first available option that she sees. Suppose the options are always displayed in the order $z - y - x$. Then the DM's choice correspondence will be as follows:

	$\{x, y, z\}$	$\{x, y\}$	$\{x, z\}$	$\{y, z\}$
$c(A, f_1)$	$\{x\}$	$\{x\}$	$\{x\}$	$\{y\}$
$c(A, f_2)$	$\{z\}$	$\{y\}$	$\{z\}$	$\{z\}$
$C_c(A)$	$\{x, z\}$	$\{x, y\}$	$\{x, z\}$	$\{y, z\}$

Table 14: Example: Choice Data for Salant-Rubinstein Application

In the above, as in Salant and Rubinstein (2008), given a set of frames, F, C_c is constructed such that $C_c(A) = \{x \mid \exists f_i \in F \text{ such that } c(A, f_i) = x\}$ for $c(A, f)$ as a choice correspondence under set A and frame f. Salant and Rubinstein (2008) present a γ-axiom under which if $x \in C_c(A) \cap C_c(B)$ then $x \in C_c(A \cup B)$, which is required for a choice with frames to be consistent with the maximization of some transitive, binary relation. This property is clearly violated in the above choice data (to see this easily, let $A = \{x, y\}$ and $B = \{y, z\}$).

This type of adaptive choice procedure is consistent with our data. Forty-eight (48 out of 222) of our subjects made no mistakes in the baseline O_5A_5 type decision problems (i.e. they are "simple optimizers" according to the above adaptive choice procedure). We define a violation of satisficing procedure as a subject choosing an option placed at position i when there is a higher-valued option placed at position $j < i$ (i.e. higher up on the screen). According to this definition, 5 of these 48 simple optimizers make no mistakes through violations of satisficing. Some 16 of the remaining 43 subjects make fewer than 60% of their mistakes through violations of satisficing. Thus, there is a sizeable (though minority) contingent of our sample who can be modeled as following the adaptive procedure described in the example above, but who will violate the central γ-axiom of Salant and Rubinstein (2008). [25]

[25]This example is similar to the two moods example (Salant and Rubinstein, 2008, page 1294).

6 Conclusion

In this paper we have presented the results of a novel experimental design to test for both i) effects of irrelevant information presented in a decision problem on choice and ii) willingness-to-pay to get rid of irrelevant information. Our main contribution is the identification of complementarities in irrelevant information presentation: both unavailable options and irrelevant attributes are necessary to generate increased mistake rates. This central result can shed light on the extant body of literature on decision theory and limited attention. Namely, we find that no leading models of choice, either rational and constrained or boundedly rational, can explain our data unless they are significantly modified. It is our hope that these results may provide direction for upcoming theoretical research intended to model choice in the presence of irrelevant information.

We should caution that our results don't suggest that not displaying such information is *always* optimal for the firm; displaying such information may be profitable for a number of reasons, including dynamic alternative sets and purchasing decisions, reference dependence (away from which we have abstracted in this work), such as the possibility that unavailable goods serve as decoy options that make certain available goods seem more attractive. However, our results do suggest that any agent considering whether to display such irrelevant information should recognize that there is a trade-off: a firm must weigh the potential immediate effect on profit relative to the effect on choice optimality on the part of the consumer that is induced by the presence of irrelevant information.

Further, we identify a "preference for simplicity". That is, for a subject who is faced with no material costs of having to ignore irrelevant information, we find that they are still willing to pay some amount to get rid of this information. This tells us that there are aspects of consumer preference in this environment that are not fully contained by measures intended to capture the notion of lost monetary value (i.e. mistake rates and time required to make a decision). It needs to be further investigated in future research how the complexity of presentation affects the algorithm used in decision making and how robust the preference for simplicity we document here is with respect to features of the decision problems used, such as color coded irrelevant information.

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Appendix A Instructions

Part 1

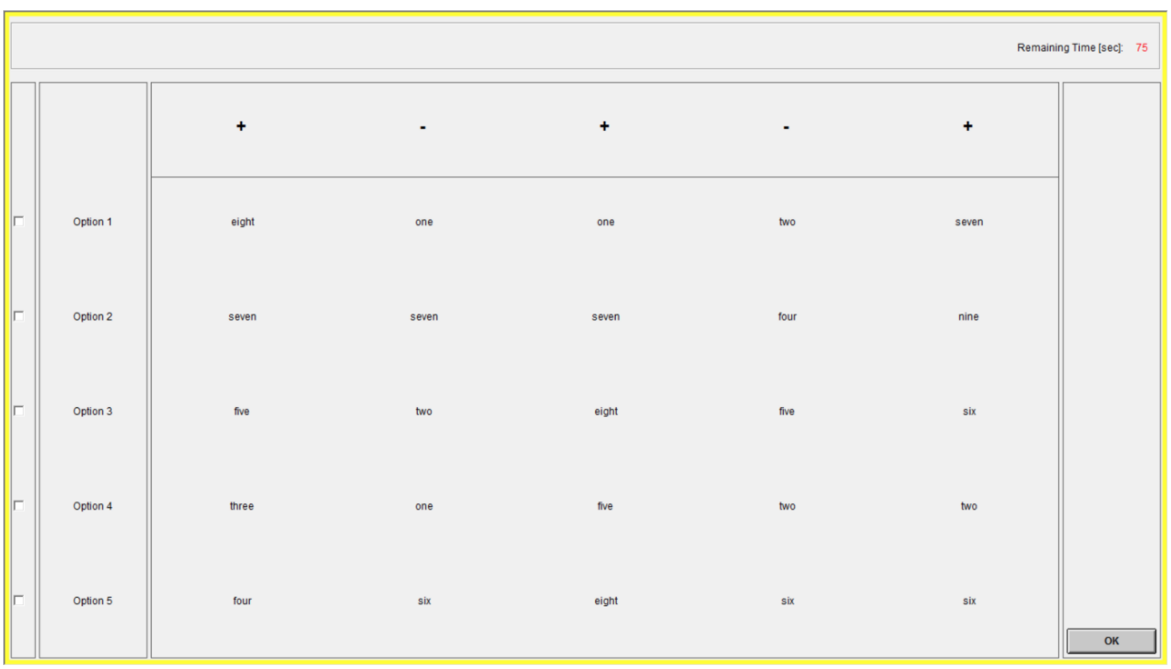
Thank you for participating in this experiment. In this session you will work alone and are not permitted to talk with any other participant. At this time, please be sure that your cell phone is turned off. At no point during the experiment are you permitted to use your cell phone or any other personal electronic device.

The Experiment

The experiment today is broken into two parts. These are the instructions for Part 1 of the experiment. At the conclusion of Part 1, the experimenter will hand out and read instructions for Part 2 before proceeding. Your earnings in Part 1 and Part 2 are independent.

This is an experiment on decision-making. In each of 40 periods, you will be asked to choose one from among a number of options. You will have at most 1 minute and 15 seconds (or 75 seconds) to make this decision in each period. Each option is described by a number of attributes. Attributes take on the numbers 1-9 with each number being equally likely to be shown. The value of each option is the result of the addition and/or subtraction of these attributes and is measured in Experimental Currency Units (or ECU). The exchange rate will be as follows: 1 USD = 10 ECU. You will know whether to add or subtract each attribute based on column headers in the displayed data. While calculating these values, you will not be permitted to use a calculator or pen and paper.

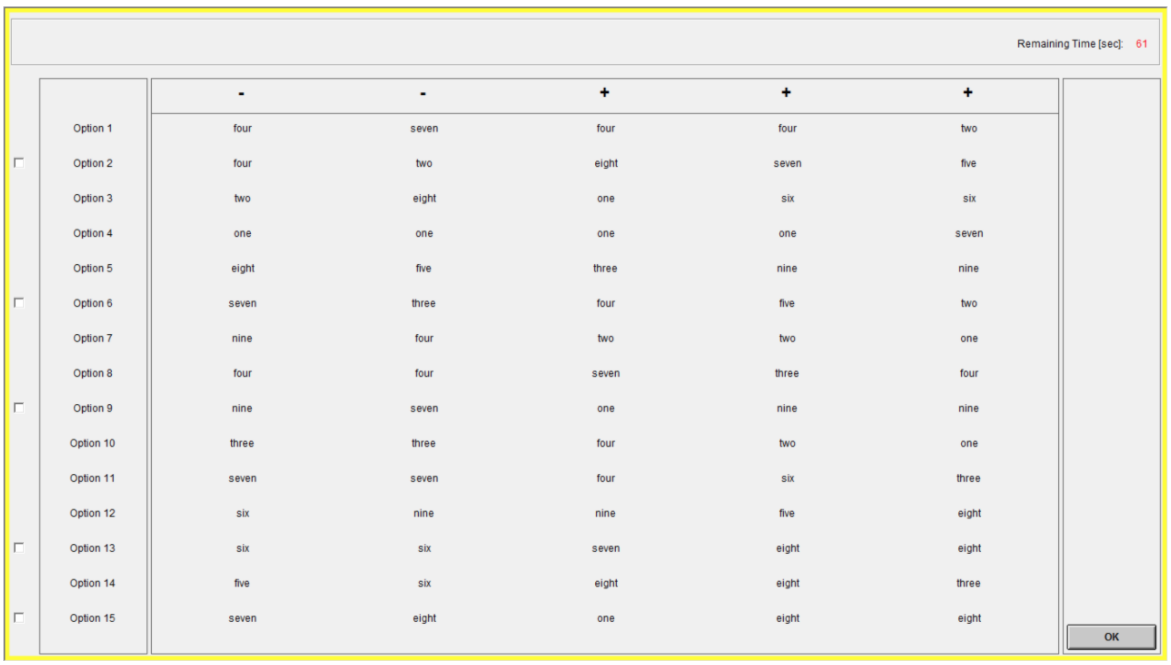
In each period, you will see a screen that looks similar to the one below:



Notice that Option 1 is accompanied by 5 numbers (shown in words) in a grid to its right. The value of Option 1 is simply the result of adding or subtracting the numbers in its corresponding row. You will know whether to add a number or subtract it based on the **plus** or **minus** sign in the column header row. Thus, the value of Option 1 is 13 ECU (or eight - one + one - two + seven = ECU). The values of Options 2-5 can be calculated in a similar way.

Variations

In each of the 40 periods, the number of available options is the same (5). However, the number of displayed options will vary. In other words, there may be some options displayed on your screen that you will not be able to select. Consider the following example:

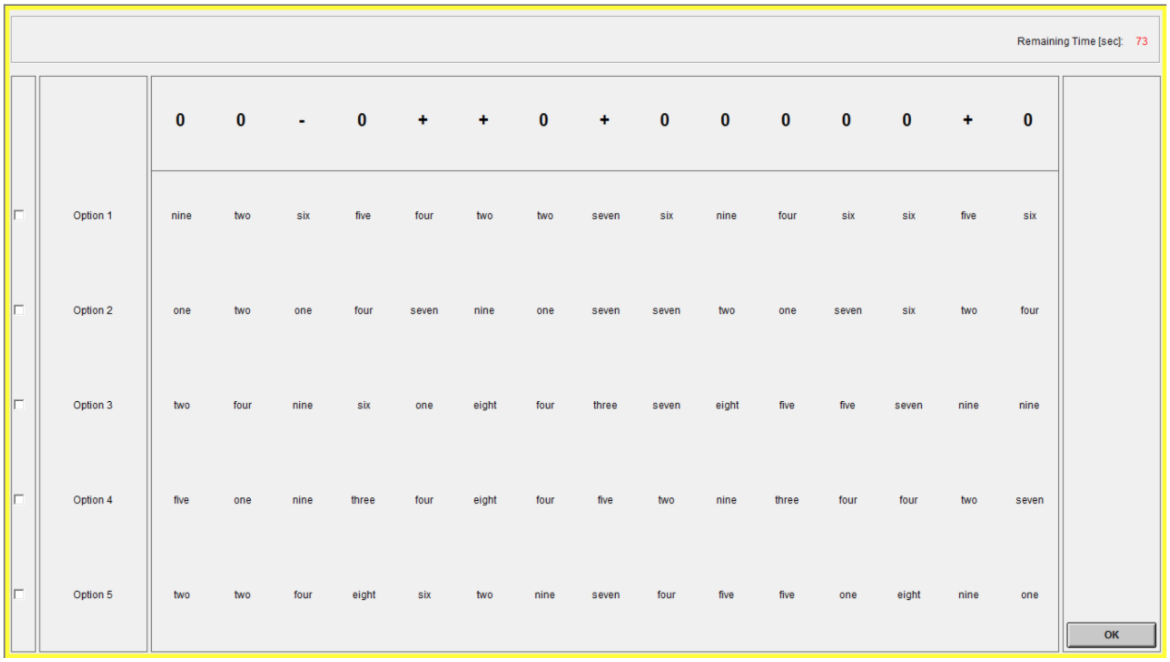

Remaining Time [sec]: 61

	-	-	+	+	+
Option 1	four	seven	four	four	two
☐ Option 2	four	two	eight	seven	five
Option 3	two	eight	one	six	six
Option 4	one	one	one	one	seven
Option 5	eight	five	three	nine	nine
☐ Option 6	seven	three	four	five	two
Option 7	nine	four	two	two	one
Option 8	four	four	seven	three	four
☐ Option 9	nine	seven	one	nine	nine
Option 10	three	three	four	two	one
Option 11	seven	seven	four	six	three
Option 12	six	nine	nine	five	eight
☐ Option 13	six	six	seven	eight	eight
Option 14	five	six	eight	eight	three
☐ Option 15	seven	eight	one	eight	eight

OK

Note that each option still has 5 attributes in the grid. However, now Option 1 cannot be selected (this can be seen from the absence of a checkbox to the left of "Option 1). You may only select one from the following: Option 2, Option 6, Option 9, Option 13, or Option 15. Which options are available will vary between periods. Also note that the value of each option is calculated as in the first example. For example, the value of Option 2 is 14 ECU (or - four - two + eight + seven + five = 14 ECU).

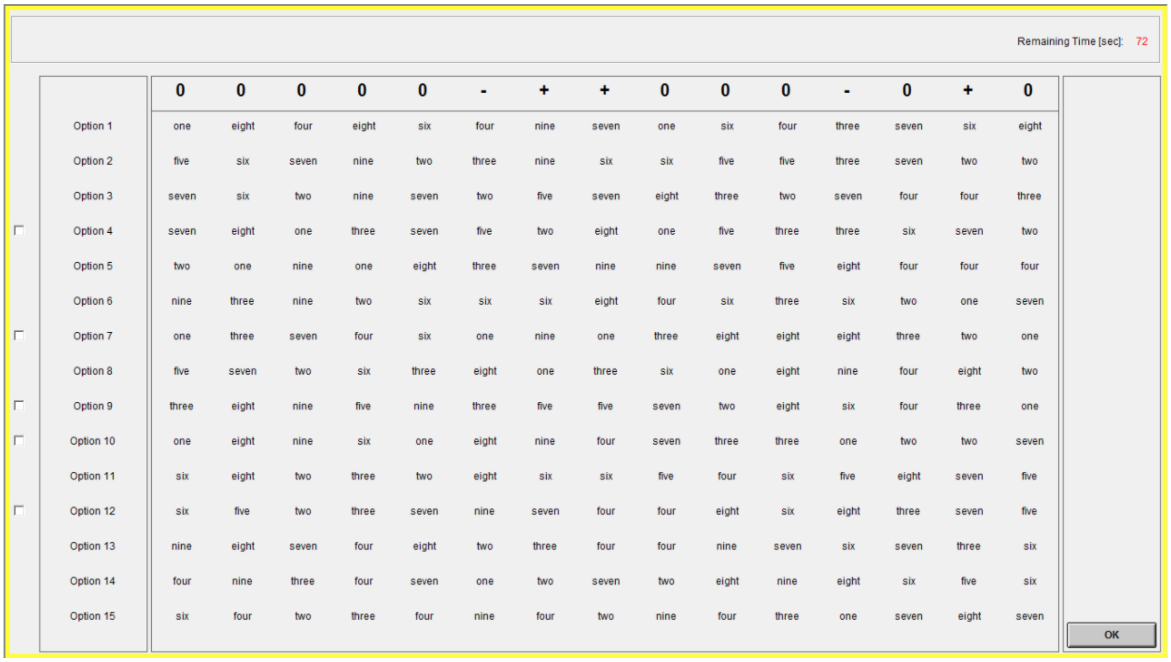
In each of the 40 periods, the number of attributes per option will vary. However, in some periods, some of these attributes may be multiplied by **zeros** instead of being added or subtracted when calculating the value of each option. Consider the following example:



		0	0	-	0	+	+	0	+	0	0	0	0	0	+	0
☐	Option 1	nine	two	six	five	four	two	two	seven	six	nine	four	six	six	five	six
☐	Option 2	one	two	one	four	seven	nine	one	seven	seven	two	one	seven	six	two	four
☐	Option 3	two	four	nine	six	one	eight	four	three	seven	eight	five	five	seven	nine	nine
☐	Option 4	five	one	nine	three	four	eight	four	five	two	nine	three	four	four	two	seven
☐	Option 5	two	two	four	eight	six	two	nine	seven	four	five	five	one	eight	nine	one

Note that all displayed options are available (you can see this from the checkbox to the left of each option label). However, there are additional attributes for each option (now there are 15). In contrast to the previous examples, some of these attributes are now multiplied by 0 instead of being added or subtracted when determining the value of each option. This can be seen from the zeros in the column header. For example, the value of Option 1 is 12 ECU (-six + four + two + seven + five = 12 ECU). Notice that in this calculation, the first and second attributes (nine and two) were not included because they have a 0 in the column header. The same is true for any value for which there is a zero in the column header. Which attributes have zeros (and pluses or minuses) will vary by period.

Finally, in some periods there will be additional attributes and unavailable options. Consider the following example:



	0	0	0	0	0	-	+	+	0	0	0	-	0	+	0
Option 1	one	eight	four	eight	six	four	nine	seven	one	six	four	three	seven	six	eight
Option 2	five	six	seven	nine	two	three	nine	six	six	five	five	three	seven	two	two
Option 3	seven	six	two	nine	seven	two	five	seven	eight	three	two	seven	four	four	three
Option 4	seven	eight	one	three	seven	five	two	eight	one	five	three	three	six	seven	two
Option 5	two	one	nine	one	eight	three	seven	nine	nine	seven	five	eight	four	four	four
Option 6	nine	three	nine	two	six	six	six	eight	four	six	three	six	two	one	seven
Option 7	one	three	seven	four	six	one	nine	one	three	eight	eight	eight	three	two	one
Option 8	five	seven	two	six	three	eight	one	three	six	one	eight	nine	four	eight	two
Option 9	three	eight	nine	five	nine	three	five	five	seven	two	eight	six	four	three	one
Option 10	one	eight	nine	six	one	eight	nine	four	seven	three	three	one	two	two	seven
Option 11	six	eight	two	three	two	eight	six	six	five	four	six	five	eight	seven	five
Option 12	six	five	two	three	seven	nine	seven	four	four	eight	six	eight	three	seven	five
Option 13	nine	eight	seven	four	eight	two	three	four	four	nine	seven	six	seven	three	six
Option 14	four	nine	three	four	seven	one	two	seven	two	eight	nine	eight	six	five	six
Option 15	six	four	two	three	four	nine	four	two	nine	four	three	one	seven	eight	seven

Note that Option 1 is **unavailable** (you can see this from the absence of any checkbox to its left). Also note that there are several columns with **zeros** in the column header. The value of Option 4 is 9 ECU (-five + two + eight -three + seven= 9 ECU). Notice that the 1st through 5th attributes were not included for Option 4 (seven, eight, one, three, and seven) since these have zeros in the column header. The same is true for any column of attributes for which there is a zero in the column header. Again, which columns have zeros (and pluses/minuses) and which options are unavailable will vary by period.

Time Limit

In each period, you have 1 minute and 15 seconds (75 seconds) to submit your choice of option. You must submit your option by checking the checkbox to its left and clicking the OK button at the bottom right of the screen. If you **do not** submit your selection by clicking the OK button prior to the end of the period (i.e. within 75 seconds of the period starting), your selection will not be submitted and **you will be paid nothing** for that period. Only by selecting an option and clicking OK prior to the end of the period will your choice be submitted for the period.

Earnings

In each period, your per-period payoff is simply the value of the option you have chosen. In each of these periods, the values for each option have been chosen so that despite being the sum of both positive and negative numbers, the **value of each available option is positive**. That is, no matter which option you choose, money will never be taken away from you. 10 periods will be chosen at random and your cash earnings will be the sum of the per-period payoffs for these 10 periods, converted to US Dollars. The exchange rate will be as follows: \$1 USD = 10 ECU. Your total cash earnings will be added to your show-up fee of $7.00 and your earnings from Part 2 of this experiment.

You will be paid your earnings privately in cash before you leave the lab.

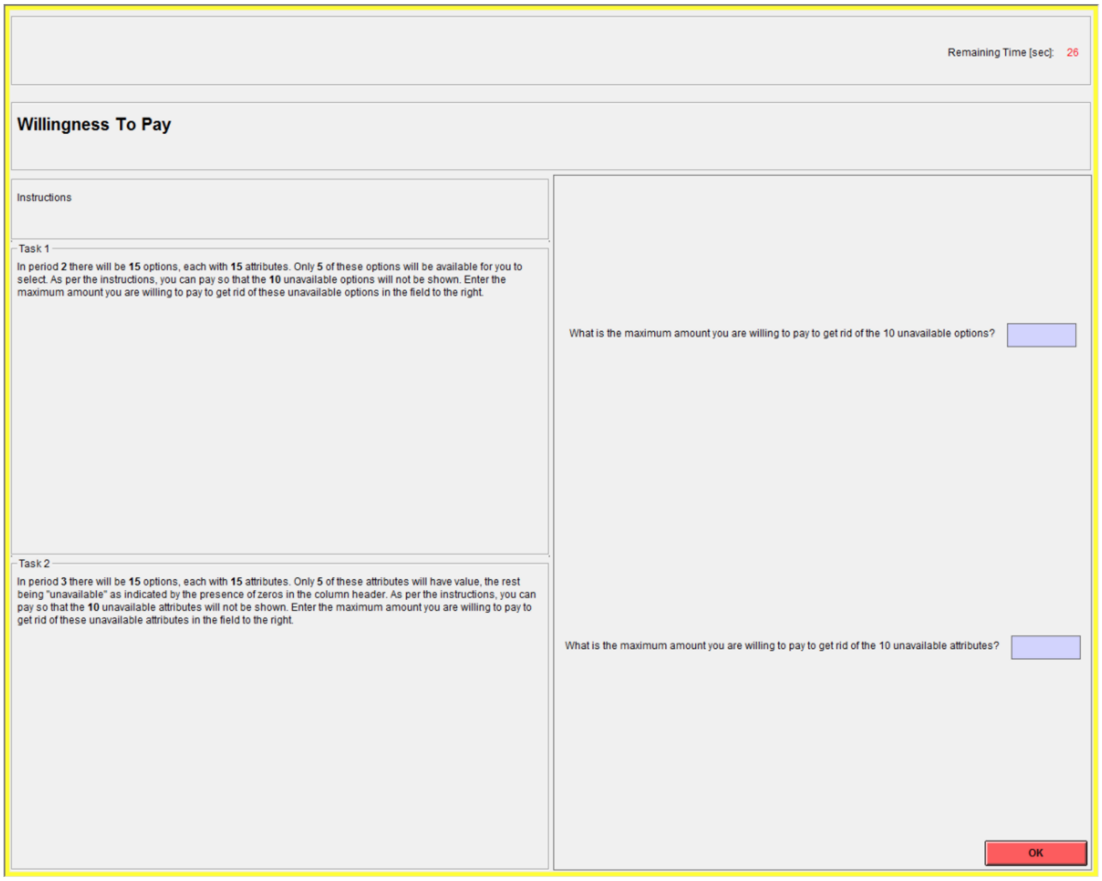
Part 2

Thank you for participating in Part 2 of the experiment.

You will be faced with 3 periods in which you make decisions: **1** period in which you will be asked to submit two numbers (explained in detail below), and **2** periods of decision environments where you will choose from among a number of options, each described by a number of attributes. Some of these options will be unavailable for you to select and some of the attributes will not have value (as indicated by the presence of a zero in the header row). However, you will have the opportunity to pay some amount (in ECU) to get rid of these unavailable options and attributes.

In period 1, you will be asked to complete **two tasks** which will affect what you see in periods 2 and 3: **Task 1** is to enter the maximum amount you are willing to pay (in ECU) to get rid of the unavailable options to be presented in period 2, and **Task 2** is to enter the maximum amount you are willing to pay to get rid of the attributes that have no value (as indicated by the zeros in the column header; these will be referred to as unavailable attributes for the remainder of the instructions) to be presented in period 3. Note that decisions in each task will correspond to outcomes in two separate subsequent periods: Task 1 affects what you see in period 2 and Task 2 affects what you see in period 3.

The screenshot below displays what this environment will look like in period 1:



For **Task 1** and **Task 2**, two random numbers will be drawn from 0 ECU to 15 ECU. These two numbers may not be the same. These will be the selling prices for getting rid of the unavailable options or unavailable attributes, respectively. If the maximum amount you are willing to pay to get rid of unavailable options that you entered for Task 1 is above the selling price for Task 1, you pay the selling price and you will not see these unavailable options in period 2. If the maximum amount you are willing to pay to get rid of unavailable attributes is higher than the selling price for Task 2, you pay the selling price and you will not see these unavailable attributes in period 3. However, if either (or both) of the selling prices are above the maximum amount you are willing to pay, entered in period 1 for Task 1 and Task 2, you pay nothing and the unavailable options or unavailable attributes will be shown in the respective period.

Note that you enter both of these numbers indicating your maximum willingness to pay to simplify the environments at the same time and **before** you know the result of either random number draw. That is, when you enter the maximum amount you are willing to pay to get rid of unavailable options, you will not know whether you have been able to get rid of unavailable attributes, and when you enter the maximum amount you are willing to pay to get rid of unavailable attributes, you will not know whether you have been able to get rid of the unavailable options. Also note that it is in your best interest not to overstate (or understate) the maximum amount you are willing to pay in either Task 1 or Task 2. Suppose you are willing to pay at most 5 ECU to get rid of either unavailable options or attributes. If the random is drawn and you enter exactly 5

ECU, there are two potential outcomes: either the number is higher than 5, in which case you pay nothing and the unavailable options or attributes will be displayed in the respective period, or the number is less than 5 , say 4 ECU. In this case, you pay the 4 ECU and the unavailable options or attributes are not shown. Note that you were willing to pay **at most** 5 ECU, but only had to pay 4 ECU.

Suppose instead that you overstate this amount in either Task 1 or Task 2 by entering, say, 6 ECU. Then it could be the case that the number drawn is 5.5, for example, which is less than 6 (which you have entered) but greater than 5, the true maximum amount that you are willing to pay. Because you have entered 6, you will pay the drawn amount, 5.5 ECU, which is more than you originally were willing to pay - you will have gotten rid of unavailable options or attributes, but paid more than the maximum amount you were willing to pay. On the other hand, suppose you understate this amount by entering 4 ECU. Then if the random number drawn is, say, 4.5 ECU, you will not be able to get rid of the unavailable options or attributes, but would be willing to pay this amount. Only by entering the actual maximum amount you are willing to pay in Task 1 and Task 2 will you both a) prevent having to pay more than this amount (by overstating) and b) prevent missing out on paying a lesser amount when it is profitable to do so (by understating).

Decision Environments

These decision environments will appear exactly as you have seen them in Part 1. Again, you will have 75 seconds to submit your decision. If you do not submit your chosen option by that time, no option will be submitted and you will be paid nothing for that period.

By default, in period 2 there will be 15 options, each with 15 attributes. Only 5 of these options will be available for you to select and only 5 of these attributes will have value (as indicated by the presence of a + or - in the column header). You can pay to have the **10 unavailable options** not displayed in this period. No matter what, each of the displayed options will have 15 attributes, 10 of which will have zeros in the column header. Whether the 10 unavailable options are displayed depends on the result of your choice in Task 1, described in detail above.

By default, in period 3 there will be 15 options, each with 15 attributes. Only 5 of these attributes will have value - the rest are unavailable (as indicated by the presence of zeros in the column header) and only 5 of these options will be available for you to select. You can pay to have the **10 unavailable attributes** not displayed in this period. No matter what, there will be 15 options displayed (5 of which will be available for selection). Whether the 10 unavailable attributes are displayed depends on the result of your choice in Task 2, described in detail above.

Payoff Calculation

In each of periods 2 and 3, your per-period payoff is simply the value of the option you have chosen. In each of these periods, the values for each option have been chosen so that despite being the sum of both positive and negative numbers, the **value of each available option is positive**. That is, no matter which option you choose, money will never be taken away from you.

Choices in all periods contribute to your payoffs for this part of the experiment. In the first period, if you are able to get rid of either unavailable options or attributes or both, the relevant random number that was drawn is subtracted from your payoffs. In each of the decision periods, the value of the option you have chosen will be added to your payoffs, with the value of each option calculated as in Part 1 of this experiment. The exchange rate will be as follows: \$1 USD = 10 ECU. Your total cash earnings will be added to your show-up fee of \$7.00 and your earnings from Part 1 of this experiment.

You will be paid your earnings privately in cash before you leave the lab.

Appendix B Additional Analyses

B.1 Additional Aggregate Results

Table 15: Mistake Rates: Excluding Timeouts

		O_5	O_{15}
A_5	Mean	0.193	0.201
	Std Error	0.013	0.013
	N	222	222
A_{15}	Mean	0.193	0.299
	Std Error	0.012	0.016
	N	222	222

$p = 0.000$ for $O_{15}A_5 \rightarrow O_{15}A_{15}$, $O_5A_{15} \rightarrow O_{15}A_{15}$, and $O_5A_5 \rightarrow O_{15}A_{15}$
$p > 0.100$ otherwise.

Table 16: Time: Timeouts Treated as Maximum Time

		O_5	O_{15}
A_5	Mean	49.200	50.405
	Std Error	0.713	0.677
	N	222	222
A_{15}	Mean	53.769	57.374
	Std Error	0.779	0.782
	N	222	222

p = 0.00 for $O_5A_5 \rightarrow O_5A_{15}$, $O_{15}A_5 \rightarrow O_{15}A_{15}$,
$O_5A_{15} \rightarrow O_{15}A_{15}$, $O_5A_5 \rightarrow O_{15}A_{15}$, and $O_{15}A_5 \rightarrow O_5A_{15}$
$p > 0.10$ for $O_5A_5 \rightarrow O_{15}A_5$

Table 17: Time: Correct

		O_5	O_{15}
A_5	Mean	48.240	49.641
	Std Error	0.727	0.662
	N	222	220
A_{15}	Mean	52.615	56.613
	Std Error	0.769	0.776
	N	222	222

p = 0.00 for $O_5A_5 \rightarrow O_5A_{15}$, $O_{15}A_5 \rightarrow O_{15}A_{15}$,
$O_5A_{15} \rightarrow O_{15}A_{15}$, $O_5A_5 \rightarrow O_{15}A_{15}$, and $O_{15}A_5 \rightarrow O_5A_{15}$
$p > 0.10$ for $O_5A_5 \rightarrow O_{15}A_5$
Conditional on Correct

B.2 Time Cost Results

Table 18: Time Regressions with Alternative Time Thresholds

	$t < 73$	$t < 70$	$t < 65$
Options	-0.830	0.433	1.719
	(-0.69)	(0.36)	(1.37)
Attributes	4.078***	3.494***	2.836**
	(3.52)	(2.93)	(2.26)
Options * Attributes	1.392**	0.958	-0.515
	(2.07)	(1.41)	(-0.74)
Period	-0.254***	-0.235***	-0.214***
	(-17.32)	(-15.81)	(-13.97)
Cognitive Score	10.30***	11.06***	12.01***
	(10.80)	(11.38)	(12.11)
Female	-2.605***	-2.429***	-2.484***
	(-7.72)	(-7.11)	(-7.13)
Economics/Business	-2.269***	-2.469***	-2.186***
	(-5.82)	(-6.25)	(-5.46)
English	-3.206***	-2.587***	-2.533***
	(-7.70)	(-6.07)	(-5.79)
Position	0.132**	0.0945*	0.0455
	(2.48)	(1.77)	(0.84)
Positive	-1.270***	-0.955***	-0.871***
	(-3.86)	(-2.88)	(-2.59)
Option Complexity	0.606**	0.259	-0.0289
	(2.05)	(0.86)	(-0.09)
Attribute Complexity	0.116	0.144	0.108
	(0.37)	(0.45)	(0.32)
Constant	53.81***	49.84***	46.05***
	(34.73)	(31.85)	(29.12)
Observations	8169	7438	6312

t statistics in parentheses

All specifications exclude timeouts

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Time Regressions with Alternative Time Thresholds
Conditional on Correct

	$t < 73$	$t < 70$	$t < 65$
Options	-0.888	0.377	1.413
	(-0.72)	(0.30)	(1.11)
Attributes	5.049***	4.802***	3.803***
	(4.22)	(3.92)	(2.98)
Options * Attributes	3.119***	2.906***	1.678**
	(4.58)	(4.24)	(2.40)
Period	-0.200***	-0.189***	-0.179***
	(-13.36)	(-12.62)	(-11.73)
Cognitive Score	6.580***	7.024***	8.251***
	(6.79)	(7.20)	(8.38)
Female	-1.263***	-1.061***	-1.244***
	(-3.70)	(-3.11)	(-3.62)
Economics/Business	-2.419***	-2.794***	-2.522***
	(-6.18)	(-7.11)	(-6.43)
English	-2.118***	-1.466***	-1.344***
	(-5.07)	(-3.47)	(-3.14)
Position	0.191***	0.142***	0.121**
	(3.51)	(2.62)	(2.23)
Positive	-0.938***	-0.808**	-0.759**
	(-2.83)	(-2.44)	(-2.29)
Option Complexity	0.529*	0.169	-0.118
	(1.73)	(0.54)	(-0.37)
Attribute Complexity	-0.0952	-0.217	-0.126
	(-0.29)	(-0.65)	(-0.36)
Constant	52.97***	50.46***	46.95***
	(34.09)	(32.48)	(30.27)
Observations	6432	5913	5036

t statistics in parentheses

All specifications exclude timeouts

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 GPA Robustness Checks

Table 20: Mistake Rate Regressions with GPA

	(1) Mistake	(2) Mistake	(3) Mistake	(4) Mistake	(5) Mistake*
Options	0.009	0.012	-0.024*	-0.074**	-0.074**
	(0.012)	(0.012)	(0.014)	(0.030)	(0.030)
Attributes	0.019	0.022*	0.015	0.013	0.013
	(0.012)	(0.012)	(0.012)	(0.029)	(0.029)
Options * Attributes	0.092***	0.083***	0.090***	0.092***	0.092***
	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
Period	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GPA		-0.223***	-0.223***	-0.223***	-0.223***
		(0.065)	(0.065)	(0.065)	(0.065)
Female		0.078***	0.078***	0.078***	0.078***
		(0.022)	(0.022)	(0.022)	(0.022)
Economics/Business		0.003	0.003	0.003	0.003
		(0.027)	(0.027)	(0.027)	(0.027)
English		-0.018	-0.018	-0.018	-0.018
		(0.024)	(0.024)	(0.024)	(0.024)
Position			0.005***	0.006***	0.006***
			(0.001)	(0.001)	(0.001)
Positive			-0.028***	-0.031***	-0.031***
			(0.009)	(0.009)	(0.009)
Attribute Complexity				0.000	0.000
				(0.008)	(0.008)
Option Complexity				0.013*	0.013*
				(0.007)	(0.007)
Observations	8880	8440	8440	8440	8440
Session FE	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Baseline: 222

11 Subjects with missing GPA excluded from models with GPA

*: Timeouts treated as mistakes

Marginal effects from logit regression specifications

Robust standard errors reported are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Time Regressions with GPA

	(1)	(2)	(3)	(4)	(5)	(6)
	Time	Time	Time	Time	Time *	Time **
Options	2.197***	2.140***	1.023**	-2.027**	-1.313	-2.027**
	(0.382)	(0.399)	(0.485)	(0.986)	(0.996)	(0.986)
Attributes	5.656***	5.736***	5.473***	4.988***	5.049***	4.988***
	(0.430)	(0.441)	(0.448)	(0.948)	(1.111)	(0.948)
Options * Attributes	1.748***	1.737***	1.981***	2.112***	3.406***	2.112***
	(0.500)	(0.518)	(0.518)	(0.521)	(0.551)	(0.521)
Period	-0.300***	-0.294***	-0.294***	-0.294***	-0.199***	-0.294***
	(0.028)	(0.029)	(0.029)	(0.029)	(0.020)	(0.029)
GPA		8.648*	8.645*	8.647*	5.988*	8.647*
		(4.454)	(4.454)	(4.454)	(3.417)	(4.454)
Female		-2.545*	-2.545*	-2.545*	-1.664	-2.545*
		(1.387)	(1.387)	(1.387)	(1.136)	(1.387)
Economics/Business		-1.135	-1.136	-1.137	-2.237*	-1.137
		(1.582)	(1.582)	(1.582)	(1.354)	(1.582)
English		-3.414**	-3.415**	-3.415**	-1.974	-3.415**
		(1.584)	(1.584)	(1.584)	(1.423)	(1.584)
Position			0.156***	0.197***	0.199***	0.197***
			(0.041)	(0.043)	(0.045)	(0.043)
Positive			-1.152***	-1.356***	-0.986***	-1.356***
			(0.277)	(0.282)	(0.273)	(0.282)
Attribute Complexity				0.128	-0.004	0.128
				(0.233)	(0.301)	(0.233)
Option Complexity				0.841***	0.591**	0.841***
				(0.230)	(0.239)	(0.230)
Observations	8880	8440	8440	8440	6332	8440
Session FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Baseline: 222

11 Subjects with missing GPA excluded from models with GPA

*: Conditional on Correct

**: Timeouts treated as Time = 75 seconds

Marginal effects reported from tobit regressions censored below by 0 and above by 75

Robust standard errors are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: WTP Regressions with GPA

	(1) WTP	(2) WTP	(3) WTP	(4) WTP > 0	(5) WTP > 0	(6) WTP > 0
Mistakes	0.413***	0.454***	0.317***	0.379***	0.405***	0.346**
	(0.102)	(0.108)	(0.119)	(0.124)	(0.127)	(0.157)
Time	0.003	0.003	0.003	0.002	0.001	0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Attributes	0.191	0.181	0.317	0.022	0.023	0.209
	(0.156)	(0.164)	(0.279)	(0.159)	(0.175)	(0.299)
High Noise	2.296*	2.470**	1.043	0.793	0.681	1.856
	(1.200)	(1.203)	(2.416)	(1.401)	(1.531)	(3.307)
Female		-0.353	-0.298		0.470	0.456
		(0.450)	(0.441)		(0.514)	(0.503)
GPA		-0.387	-0.454		-0.708	-0.662
		(1.179)	(1.151)		(1.086)	(1.098)
High Noise * Mistakes			0.292			0.117
			(0.205)			(0.248)
High Noise * Time			0.001			-0.002
			(0.004)			(0.005)
High Noise * Attributes			-0.255			-0.436
			(0.334)			(0.339)
Constant	0.394	0.580	1.059	-0.038	0.485	0.240
	(1.281)	(1.436)	(1.735)	(1.363)	(1.698)	(1.839)
Observations	444	422	422	386	366	366
Session FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

Number of Subjects in Baseline: 222

11 Subjects with missing GPA dropped from Models 2-6

Additional 29 Subjects dropped from Models 4 - 6 because session FE perfectly predicts WTP > 0

Models 1 - 3: Tobit regression specifications with lower limit of 0 and upper limit of 15

Models 4-6: Logit regression specifications

Robust standard errors reported are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.4 Regressions Under Alternative Complexity Measures

In Section 3, we introduce a complexity measure to determine whether the mistake rate in each treatment depended on the number of "skips" in the evaluation process for either attributes or options. In this appendix, we present regression results where we investigate whether mistakes depend on attribute and option complexity under alternative versions of this measure.

First, we introduce "Opt Comp w/ 0" and "Att Comp w/ 0" measures that are the measures we used previously in the body of the text, but including leading and trailing zeros. Second, we introduce "Opt Comp 1st" and "Opt Comp 2nd," with the analogous measures defined for Attributes. These measures take our aggregate measures and split them into the "first half" and "second half" of the evaluation process in each dimension. In other words, "Opt Comp 1st" is "the number of skips in Options for the first 7 Options" and "Opt Comp 2nd" is "the number of skips in Options for the last 8 Options." "Att Comp 1st" and "Att Comp 2nd" are defined analogously.

The hypothesis here is that it is possible, given order effects documented by the effects of the Position variable in previous regressions, that complexity might matter more for the first several options/attributes than for later options/attributes. We find that this is the case for the mistake rate regressions as the coefficient of Opt Comp 1st is higher than that of Opt Comp 2nd and the coefficient of Att Comp 1st is higher than its counterpart in the relevant columns of Table 23. This is also the case for the time regressions in Table 24.

In each of the tables below, models are conducted for observations from our main experiment. Each is restricted to the relevant subsample where the complexity measure is meaningful, as indicated in the last row of the table.

Table 23: Mistake Rate Regressions

	(1) Mistake	(2) Mistake	(3) Mistake	(4) Mistake	(5) Mistake	(6) Mistake
Period	0.000	0.000	0.000	0.000	0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Cognitive Score	-0.218***	-0.275***	-0.227***	-0.234***	-0.275***	-0.226***
	(0.063)	(0.069)	(0.069)	(0.064)	(0.069)	(0.069)
Female	0.077***	0.086***	0.076***	0.078***	0.086***	0.077***
	(0.021)	(0.023)	(0.024)	(0.022)	(0.023)	(0.024)
Economics/Business	-0.008	-0.012	-0.013	-0.010	-0.012	-0.013
	(0.025)	(0.028)	(0.027)	(0.026)	(0.028)	(0.027)
English	-0.002	-0.002	-0.007	-0.001	-0.002	-0.007
	(0.022)	(0.027)	(0.024)	(0.023)	(0.027)	(0.024)
Opt Comp w/ 0		0.002		0.020***		
		(0.008)		(0.003)		
Att Comp w/ 0			0.016**	0.019***		
			(0.008)	(0.003)		
Opt Comp 1st					0.026***	
					(0.010)	
Opt Comp 2nd					-0.002	
					(0.009)	
Att Comp 1st						0.038***
						(0.009)
Att Comp 2nd						-0.024**
						(0.011)
Observations	8555	4269	4219	6393	4269	4219
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
Decision Problems	All	$O_{15}A_5$, $O_{15}A_{15}$	O_5A_{15} , $O_{15}A_{15}$	$O_{15}A_5$, $O_{15}A_{15}$, O_5A_{15}	$O_{15}A_5$, $O_{15}A_{15}$	O_5A_{15} , $O_{15}A_{15}$

Standard errors in parentheses

Number of Subjects in Each Model: 222

Marginal effects from logit regression specifications

Robust standard errors reported are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Time Regressions

	(1) Time	(2) Time	(3) Time	(4) Time	(5) Time	(6) Time
Period	-0.264***	-0.239***	-0.272***	-0.252***	-0.238***	-0.273***
	(0.026)	(0.028)	(0.029)	(0.026)	(0.028)	(0.029)
Cognitive Score	9.937**	9.595**	13.987***	11.183***	9.597**	13.997***
	(4.142)	(4.222)	(4.475)	(4.249)	(4.222)	(4.471)
Female	-2.537*	-2.540*	-3.192**	-2.691*	-2.539*	-3.182**
	(1.337)	(1.364)	(1.475)	(1.374)	(1.363)	(1.475)
Economics/Business	-2.302	-2.328	-2.048	-2.159	-2.328	-2.048
	(1.585)	(1.596)	(1.720)	(1.613)	(1.596)	(1.718)
English	-3.134**	-3.169**	-3.393**	-3.174**	-3.171**	-3.393**
	(1.535)	(1.513)	(1.607)	(1.528)	(1.513)	(1.606)
Opt Comp w/ 0		0.701***		0.758***		
		(0.207)		(0.072)		
Att Comp w/ 0			0.593***	1.411***		
			(0.219)	(0.100)		
Opt Comp 1st					0.890***	
					(0.298)	
Opt Comp 2nd					0.696***	
					(0.252)	
Att Comp 1st						0.676***
						(0.213)
Att Comp 2nd						0.156
						(0.344)
Observations	8555	4269	4219	6393	4269	4219
Session FE	Yes	Yes	Yes	Yes	Yes	Yes
Decision Problems	All	$O_{15}A_5$, $O_{15}A_{15}$	O_5A_{15} , $O_{15}A_{15}$	$O_{15}A_5$, $O_{15}A_{15}$, O_5A_{15}	$O_{15}A_5$, $O_{15}A_{15}$	O_5A_{15} , $O_{15}A_{15}$

Standard errors in parentheses

Number of Subjects in Each Model: 222

Marginal effects reported from tobit regressions censored below by 0 and above by 75

Robust standard errors are clustered at the Subject level

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.5 Additional Welfare Measures

In order to investigate whether our main result was robust to specifications of welfare loss other than the mistake rate, we additionally conducted analyses on the rank of the final choice. The variable Rank runs from 1, indicating that the worst available option is chosen, to 5, indicating that the best available option is chosen. In some decision problems, several available options (other than the best) had the same monetary value. For these observations, the midpoint of the relevant Rank was used (e.g. if the 2nd and 3rd best available options were of the same monetary value, they were both recorded as Rank of 2.5). Our results are robust to i) dropping all observations with such a "tie" and iii) rounding up such "ties" and these results are available upon request.

Table 25 reports the results of several regression specifications where the dependent variable is Rank. Robust across all specifications is the negative coefficient on Options * Attributes, indicating that the interaction between Options and Attributes causes subjects to choose lower ranked options.

Additionally, we can measure the amount of ECU lost as a result of a mistake. Our data generation process results in variance across decision problem types in terms of "possible loss." Average distance in monetary terms of each available option relative to the best option in a given decision problem differs significantly when we change the type of decision problem. We therefore do the following normalization: we take the actual loss for the choice of a subject (i.e. Maximum Value - Value of Choice) and divide it by the Mean Value of available options in the given decision problem.

We replicate our main results using this normalized loss measure with regressions included in Table 26. The main message of the regressions included in Table 26 and the mistake rate regressions in Table 4 is very similar. Normalized loss regressions further indicate the role of different types of irrelevant information and subject heterogeneity on monetary loss due to suboptimal choice.

Table 25: Rank Regressions

	(1) Rank	(2) Rank	(3) Rank	(4) Rank
Options	-0.197*	-0.193*	0.181	0.448
	(0.113)	(0.113)	(0.125)	(0.277)
Attributes	-0.074	-0.081	0.006	0.259
	(0.113)	(0.113)	(0.114)	(0.264)
Options * Attributes	-0.680***	-0.676***	-0.766***	-0.775***
	(0.171)	(0.172)	(0.171)	(0.173)
Period	-0.004	-0.004	-0.004	-0.004
	(0.005)	(0.004)	(0.004)	(0.004)
Cognitive Score		2.204***	2.201***	2.203***
		(0.618)	(0.617)	(0.617)
Female		-0.745***	-0.744***	-0.743***
		(0.217)	(0.217)	(0.217)
Economics/Business		0.085	0.084	0.084
		(0.259)	(0.259)	(0.259)
English		-0.004	0.005	0.005
		(0.226)	(0.225)	(0.225)
Position			-0.048***	-0.050***
			(0.011)	(0.012)
Positive			0.380***	0.394***
			(0.079)	(0.080)
Attribute Complexity				-0.074
				(0.071)
Option Complexity				-0.076
				(0.069)
Observations	8555	8555	8555	8555

Standard errors in parentheses

Number of Subjects in Each Model: 222

Tobit regression specifications with lower limit = 1, upper limit = 5

Robust standard errors reported are clustered at the Subject level

Session level fixed effects included

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26: Normalized Loss Regressions

	(1)	(2)	(3)	(4)
	Loss	Loss	Loss	Loss
Options	0.107**	0.106**	-0.077	-0.218*
	(0.050)	(0.050)	(0.055)	(0.118)
Attributes	0.060	0.064	0.020	0.003
	(0.050)	(0.051)	(0.051)	(0.117)
Options * Attributes	0.254***	0.252***	0.297***	0.303***
	(0.076)	(0.077)	(0.077)	(0.077)
Period	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Cognitive Score		-0.977***	-0.974***	-0.974***
		(0.275)	(0.274)	(0.274)
Female		0.339***	0.338***	0.338***
		(0.096)	(0.096)	(0.096)
Economics/Business		-0.042	-0.042	-0.042
		(0.114)	(0.114)	(0.114)
English		0.015	0.011	0.011
		(0.099)	(0.099)	(0.099)
Position			0.023***	0.025***
			(0.005)	(0.005)
Positive			-0.192***	-0.201***
			(0.034)	(0.034)
Attribute Complexity				0.004
				(0.031)
Option Complexity				0.039
				(0.030)
Observations	8555	8555	8555	8555

Standard errors in parentheses

Number of Subjects in Each Model: 222

Tobit regression specifications with lower limit = 0, upper limit = 3.5

Robust standard errors reported are clustered at the Subject level

Session level fixed effects included

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix C Robustness Checks

For robustness, we conducted an additional six sessions of our main tasks under alternative designs. In this appendix, we present the relevant results used for robustness checks with this additional dataset.

C.1 Aggregate Results: 8 x 8

Table 27: Mistake Rates: Including Timeouts

	O_5	O_8
A_5		
Mean	0.168	0.160
Std Error	0.022	0.021
N	62	62
A_8		
Mean	0.131	0.242
Std Error	0.021	0.022
N	62	62

$p < 0.01$ for $O_5A_8 \to O_8A_8$, $O_8A_5 \to O_8A_8$, $O_5A_5 \to O_8A_8$
$p > 0.10$ otherwise

Table 28: Mistake Rates: Excluding Timeouts

	O_5	O_8
A_5		
Mean	0.159	0.147
Std Error	0.022	0.021
N	62	62
A_8		
Mean	0.108	0.223
Std Error	0.021	0.021
N	62	62

$p < 0.10$ for $O_8A_5 \to O_5A_8$
$p < 0.05$ for $O_5A_5 \to O_8A_8$ and $O_5A_5 \to O_5A_8$
$p < 0.01$ for $O_8A_5 \to O_8A_8$ and $O_5A_8 \to O_8A_8$
$p > 0.10$ otherwise

Table 29: Time: No Timeouts

	O_5	O_8
A_5		
Mean	48.935	49.586
Std Error	1.148	1.126
N	62	62
A_8		
Mean	51.754	55.345
Std Error	1.276	1.180
N	62	62

$p < 0.10$ for $O_5A_5 \to O_5A_8$

$p < 0.05$ for $O_5A_8 \to O_8A_8$

$p < 0.01$ for $O_8A_5 \to O_8A_8$ and $O_5A_5 \to O_8A_8$

Table 30: Time: Timeouts as Maximum Time

	O_5	O_8
A_5		
Mean	49.124	49.900
Std Error	1.165	1.141
N	62	62
A_8		
Mean	52.289	55.784
Std Error	1.266	1.180
N	62	62

$p < 0.05$ for $O_5A_8 \to O_8A_8$ and $O_5A_5 \to O_5A_8$

$p < 0.01$ for $O_8A_5 \to O_8A_8$ and $O_5A_5 \to O_8A_8$

Table 31: Time: Correct

	O_5	O_8
A_5		
Mean	48.733	49.209
Std Error	1.096	1.078
N	62	62
A_8		
Mean	51.904	54.914
Std Error	1.207	1.279
N	61	62

$p < 0.10$ for $O_8A_5 \to O_5A_8$

$p < 0.05$ for $O_5A_8 \to O_8A_8$ and $O_5A_5 \to O_5A_8$

$p < 0.01$ for $O_8A_5 \to O_8A_8$ and $O_5A_5 \to O_8A_8$

Table 32: Timeouts

	O_5	O_8
A_5		
Mean	0.010	0.015
Std Error	0.005	0.005
N	62	62
A_8		
Mean	0.024	0.026
Std Error	0.006	0.009
N	62	62

$p < 0.10$ for $O_5 A_5 \rightarrow O_8 A_8$

$p < 0.05$ for $O_5 A_5 \rightarrow O_5 A_8$

C.2 WTP

Table 33: Willingness to Pay: 8 x 8

	Low Noise		High Noise	
	$WTP(A\|O_5)$	$WTP(O\|A_5)$	$WTP(A\|O_8)$	$WTP(O\|A_8)$
Mean	3.100	2.800	3.219	2.562
Std Error	0.568	0.554	0.588	0.479
N	30	30	32	32

$p > 0.10$ for all relevant comparisons

Table 34: WTP Greater Than Zero: 8 x 8

	Low Noise		High Noise	
	$WTP(A\|O_5)$	$WTP(O\|A_5)$	$WTP(A\|O_8)$	$WTP(O\|A_8)$
Mean	0.633	0.600	0.656	0.625
Std Error	0.089	0.091	0.085	0.087
N	30	30	32	32

$p > 0.10$ for all relevant comparisons

C.3 Alt-High Noise Results

Table 35: Willingness to Pay: 15 x 15

	$WTP(O_{15}A_{15}) \to WTP(O_5A_5)$
Mean	5.452
Std Error	0.819
N	31

Excludes one observation where WTP = 70 ECU

Table 36: WTP Greater Than Zero

	$WTP(O_{15}A_{15}) \to WTP(O_5A_5)$
Mean	0.844
Std Error	0.065
N	32