**ORIGINAL PAPER** 



# 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.

**Keywords** Presentation set  $\cdot$  Bounded rationality  $\cdot$  Simplicity  $\cdot$  Costly ignorance  $\cdot$  Free disposal of information

JEL Classification D03 · D83 · D91

## **1** Introduction

In many decision problems, unavailable options along with irrelevant attributes are presented to decision makers. For example, consider a new employee of a large firm in the United States who must choose a health insurance plan. Among the many

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plans listed in their benefits handbook are some plans that are only available to employees of a high enough rank (e.g. team leads, managers, vice presidents) and so are "unavailable" to this new employee. Nevertheless, they can see premiums, coverage amounts, co-pays, etc. for these unavailable plans in the same way that they can see this information for plans that the employee can actually choose. Additionally, even among these plans some of this information might not be valuable. For example, if this new employee takes no regular specialty medication and always chooses generic medications, coverage for branded prescription drugs is irrelevant.

Consider some additional examples of unavailable alternatives:<sup>1</sup> In a restaurant menu, unavailable items may still be listed in the menu with a "sold out" note. 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 carbohydrates even when they are 0%, such as for bottled water. Smartphones will list available service providers, even though this set will not vary across available smartphones.<sup>2</sup> 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 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 (hereinafter 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

<sup>&</sup>lt;sup>1</sup> 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.

 $<sup>^{2}</sup>$  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.

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.<sup>3</sup> 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"

<sup>&</sup>lt;sup>3</sup> Oprea (2019) also looks at "complexity" of decision rules, though in a different context than what we consider herein.

to a DM than others, causing them to be overweighted in the decision-making process (see Bordalo et al. (2012, 2013, 2016)). Some other models of search in multiattribute settings are also based on *available* options and attributes.<sup>4</sup> 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.<sup>5</sup>

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. We discuss our results and some of the implications thereof in Sect. 5 and Sect. 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 min 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 Electronic supplementary material 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

<sup>&</sup>lt;sup>4</sup> See Klabjan et al. (2014), Sanjurjo (2017), Richter (2017), for example.

<sup>&</sup>lt;sup>5</sup> 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), Bordalo et al. (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.

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 Electronic supplementary material 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. 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.<sup>6</sup>

This choice environment takes the tradeoff between attributes in many real-world choice situations as given and extends this to a well-defined and simplified laboratory setting. Recall the health insurance choice example that we introduced in the Introduction. It is commonplace for a consumer to, for example, ask herself "how much higher a premium am I willing to pay for a plan that includes coverage for acupuncture," thereby explicitly weighing the substitution between the coverage for acupuncture and savings on the premium. Our experimental environment captures this aspect of valued information using simple weights of 1 and -1 in a linear (perfect substitute) aggregation rule (for attributes that have utility and disutility, respectively) and therefore closely resembles the design of Gabaix et al. (2006) and Caplin et al. (2011).<sup>7</sup>

In the same setting, there are also likely attributes for which a consumer can see information which are not valued. For example, a consumer who always purchases generic drugs will not care about the coverage for branded prescription drugs or a brand-unconscious consumer might say "I don't care whether my health insurance provider is BlueCross or Kaiser Permanente, so I should ignore that information." While she sees the information on brand prescription coverage or insurance provider (as it is displayed invariably with any plan description) on a plan, she will optimally ignore that displayed information, treating it as irrelevant to her current decision. This is captured in our experiment by using coefficients of 0 in the header for socalled "irrelevant attributes" (information that has no utility consequence and should

<sup>&</sup>lt;sup>6</sup> 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.

<sup>&</sup>lt;sup>7</sup> Note that our design differs slightly from 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 value. 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 irrelevant information is *displayed*, but not *valued*. 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.

0	one	nine
ı	six	seven
0	two	one
0	five	three
÷	$\operatorname{eight}$	eight
0	two	two
0	$\sin$	six
0	two	two
0	four	nine
+	four	five
0	seven	one
0	one	six
0	$_{\rm three}$	two
+	four	eight
+	three	one
	Option 1	Option 2

Fig. 1 Options with 5 relevant and 10 irrelevant attributes

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be ignored). Additionally, the same consumer might see information for plans for which she is not eligible due to her position in the company. These "unavailable options" should also then be ignored. As it so happens, our decision screens closely resemble the United States Office of Personnel Management Federal Employee Health Benefit plan comparison tool, where employees see a grid of coverage and cost related attributes (some irrelevant) for various plans (some unavailable based on employee status).<sup>8</sup>"

In Fig. 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  $\{1, 2, ..., 9\}$ ) 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.

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. We chose to add ten unavailable options and/or irrelevant attributes in problems with irrelevant information in part due to screen size limitations; adding any additional options/attributes would introduce the need for scrolling, text size variation across decision problems, and possibly other changes that would introduce confounds to our design. We conjectured that having twice as much irrelevant information than the relevant information in each dimension is sizable.

In each decision problem, the subjects needed to choose one of the five available options in 75 s.<sup>9</sup> 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.<sup>10</sup>. Each subject saw the same set of 40 decision problems, differing only in the order in which they were encountered.<sup>11</sup> The order of the

<sup>&</sup>lt;sup>8</sup> OPM plan comparison tool: https://www.opm.gov/healthcare-insurance/healthcare/plan-information/ compare-plans/.

<sup>&</sup>lt;sup>9</sup> Subjects earned a payoff of \$0 if they didn't make a choice within 75 s.

<sup>&</sup>lt;sup>10</sup> 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 Sect. 4 and Electronic supplementary material Appendices D.1 and D.2

<sup>&</sup>lt;sup>11</sup> The complete set of decision problems is available upon request.

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)  $O_{15}A_{15} \rightarrow O_{15}A_5$ .<sup>12</sup> 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 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.

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 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.

<sup>&</sup>lt;sup>12</sup> 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 Sect. 4 and included in Electronic supplementary material Appendix D.3.

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 s. 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  $O_i A_i$  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  $O_{5}A_{15}$ ), 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 17 in Electronic supplementary material Appendix B.1.

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

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	$O_{15}A_{15} \rightarrow O_5A_{15} \text{ and } O_{15}A_{15} \rightarrow O_{15}A_5$

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. 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 18 and 19 in Electronic supplementary material Appendix B.1, respectively; results are not qualitatively different from those presented in Table 3.<sup>13</sup>

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 s 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.

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

<sup>&</sup>lt;sup>13</sup> 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 19, the mean time taken to choose correctly is substantially less than the time limit of 75 s 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.



 $p = 0.000 \quad \text{for} \quad O_{15}A_5 \to O_{15}A_{15}, \quad O_5A_{15} \to O_{15}A_{15}, \quad \text{and} \quad O_5A_5 \to O_{15}A_{15}$ 

p > 0.100 otherwise

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.<sup>14</sup>

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 within the parameter range used in our experiments, 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.<sup>15</sup>
- 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

<sup>&</sup>lt;sup>14</sup> 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.

<sup>&</sup>lt;sup>15</sup> Additional results using alternative parameters that are discussed in Sect. 4 and Electronic supplementary material Appendix D 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).

		<i>O</i> <sub>5</sub>	<i>O</i> <sub>15</sub>
$A_5$	Mean	48.605	49.926
	Std error	0.712	0.680
	Ν	222	222
$A_{15}$	Mean	52.935	56.365
	Std error	0.780	0.810
	Ν	222	222

 $\begin{array}{l} p=0.00 \ \, \mbox{for} \ \ O_5A_5 \to O_5A_{15}, \ \ O_{15}A_5 \to O_{15}A_{15}, \ \ O_{5}A_{15} \to O_{15}A_{15}, \\ O_5A_5 \to O_{15}A_{15}, \ \ \ \ \ \ \ \ \ \ \ O_{5}A_5 \to O_{15}A_5 \to O_{15}A_5 \end{array}$ 

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. 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, "Period" is the period in which the decision problem was presented, and "Period<sup>2</sup>" is its square. 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  $j \in \{\text{GPA}, \text{SAT}, \text{ACT}\}$ ,  $\mu_i^j$  be the value of variable *j* for subject *i*,  $\mu_{max}^j$ be the maximum value of *j* in the subject population, and  $\mu_{min}^j$  be the minimum value of *j* in the subject population. Then let  $\mu_i^j$ , 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  $j \in \{\text{GPA}, \text{SAT}, \text{ACT}\}$ , 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

Table 3 Time: no timeouts

Table 4	Mistake rate	e regressions
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	(1)	(2)	(3)	(4)	(5)
	Mistake	Mistake	Mistake	Mistake	Mistake <sup>a</sup>
Options	0.010	0.010	- 0.023*	- 0.049*	- 0.061**
	(0.011)	(0.011)	(0.013)	(0.028)	(0.029)
Attributes	-0.000	0.000	-0.007	- 0.011	0.017
	(0.012)	(0.012)	(0.012)	(0.028)	(0.028)
Options * Attributes	0.086***	0.086***	0.093***	0.094***	0.099***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Period	- 0.007***	-0.007***	- 0.007***	- 0.007***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Period <sup>2</sup>	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cognitive score		-0.217***	- 0.218***	- 0.218***	-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		- 0.003	- 0.003	- 0.003	- 0.013
		(0.022)	(0.022)	(0.022)	(0.023)
Position			0.005***	0.005***	0.006***
			(0.001)	(0.001)	(0.001)
Positive			- 0.030***	- 0.031***	-0.031***
			(0.008)	(0.008)	(0.008)
Attribute complexity				0.001	- 0.002
				(0.007)	(0.007)
Option complexity				0.007	0.009
				(0.007)	(0.007)
Observations	8555	8555	8555	8555	8880
Session FE	Yes	Yes	Yes	Yes	Yes

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

<sup>a</sup>Timeouts treated as mistakes

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 Electronic supplementary material 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.<sup>16</sup> 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 7, 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 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 Fig. 1 above, has a "Attribute Complexity" equal to 3 (since there are essentially three groups of irrelevant

<sup>&</sup>lt;sup>16</sup> 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.

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 7, when "Options" ("Attributes") is equal to 1, "Option Complexity" ("Attribute Complexity") varies between 2 and 5 in the realized data.<sup>17</sup>

The regressions in Table 4 are conducted on the sub-sample where the submission is made in under 75 s. 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 9.9 percentage points (in Model 5). 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 whether this main result is robust to specifications of welfare loss other than the mistake rate, we conducted analyses using two additional welfare measures: Normalized Monetary Loss and the Rank of the final choice. These results are displayed in Tables 5 and 6, respectively, and the results are qualitatively similar to those found in Table 4 for the mistake rate.

Because of differences in option values across decision problem treatments as a result of the data generation process, we used the following normalization for this loss measurement in Table 5: we take the actual loss for the choice of the subject (i.e. the difference between the Maximum Option Value in Decision Problem and the Value of Choice) and divide it by the difference between the Maximum Option Value and the Mean Value of available options in the decision problem. The variable Rank used in Table 6 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).<sup>18</sup> We see that the qualitative message of these regressions is similar to our mistake rate analysis: subjects take on more normalized monetary loss and choose lower ranked options when both unavailable Options and irrelevant Attributes are present. In Tables 4, 5, and 6, the coefficients of Period and Period<sup>2</sup> indicate that Period's effect on suboptimal choice has a U-shape (coefficients on Period and Period<sup>2</sup> are significant and negative and positive, respectively, in Tables 4 and 5 and the reverse in Table 6). Hence, the overall effect of learning would not undo our main result, had we only included more Periods and decision problems.<sup>19</sup>

<sup>&</sup>lt;sup>17</sup> We further explore alternative complexity measures for relevant subsamples of this dataset in Electronic supplementary material Appendix B.4.

<sup>&</sup>lt;sup>18</sup> 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.

<sup>&</sup>lt;sup>19</sup> See Table 27 and Fig. 3 in Electronic supplementary material Appendix C for learning trends across decision problem types.

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 7. Observations are censored below by 0 and above by 75 s.<sup>20</sup> 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 s (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 interaction effects: that having both unavailable options and irrelevant attributes increases time spent by between 1.729 s (in Model 2) and 3.481 s (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.<sup>21</sup>

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.

A comparison of the results on the mistake rate and time spent can potentially illuminate some of the mechanisms involved in decision making in this experiment. For example, we see that both Options and Attributes increase Time spent in a decision problem, but not the Mistake rate. Further, consider the fact that the average number of seconds spent in an  $O_5A_5$  decision problem is approximately 48.6 s (seen in Table 3), indicating that with no irrelevant information, subjects have "time to spare" on average. With the addition of irrelevant information in either direction alone, subjects might then spend more time (as indicated in Table 7), but that the additional time required to find the best option in the presence of irrelevant information might not push the subject over the 75 second time limit. The evidence in Tables 4 and 7 are suggestive of such a mechanism. Furthermore, note that Option Complexity significantly increases Time spent in the decision problem, but not the

<sup>&</sup>lt;sup>20</sup> To investigate the sensitivity of our results to this choice, we conduct further regressions using lower time thresholds. These can be found in Tables 20 and 21 of Electronic supplementary material Appendix B.2.

<sup>&</sup>lt;sup>21</sup> 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	Normalized	loss	regressions
Tuble 5	1 tor manifed	1000	regressions

	(1)	(2)	(3)	(4)
	Loss	Loss	Loss	Loss
Options	0.114**	0.113**	- 0.078	- 0.183
	(0.050)	(0.050)	(0.054)	(0.117)
Attributes	0.063	0.066	0.021	0.010
	(0.051)	(0.051)	(0.051)	(0.116)
Options * Attributes	0.248***	0.245***	0.293***	0.297***
	(0.077)	(0.077)	(0.077)	(0.077)
Period	- 0.026***	-0.027***	- 0.030***	- 0.029***
	(0.007)	(0.007)	(0.007)	(0.007)
Period <sup>2</sup>	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Cognitive score		-0.978***	- 0.975***	- 0.976***
		(0.276)	(0.275)	(0.275)
Female		0.340***	0.339***	0.339***
		(0.097)	(0.096)	(0.096)
Economics/Business		-0.042	- 0.042	-0.041
		(0.114)	(0.114)	(0.114)
English		0.014	0.009	0.010
		(0.099)	(0.099)	(0.099)
Position			0.024***	0.026***
			(0.005)	(0.005)
Positive			- 0.201***	- 0.207***
			(0.034)	(0.034)
Attribute complexity				0.003
				(0.031)
Option complexity				0.029
				(0.030)
Observations	8555	8555	8555	8555
Session FE	Yes	Yes	Yes	Yes

Number of Subjects in Each Model: 222

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

Robust standard errors reported are clustered at the Subject level

p < 0.10, p < 0.05, p < 0.01

mistake rate (see models 4–6 in Table 7 and models 4–5 in Table 4, respectively). This would also indicate that in the presence of increased decision problem complexity, subjects spend additional time, but that this additional time spent does not cause the time constraint to be binding and hence, does not make the subject more likely to choose sub-optimally due to the increased complexity.

	(1)	(2)	(3)	(4)
	Rank	Rank	Rank	Rank
Options	- 0.215*	-0.211*	0.185	0.363
	(0.112)	(0.113)	(0.124)	(0.274)
Attributes	- 0.079	-0.087	0.004	0.244
	(0.114)	(0.114)	(0.114)	(0.264)
Options * Attributes	- 0.664***	- 0.660***	- 0.756***	- 0.761***
	(0.171)	(0.172)	(0.171)	(0.172)
Period	0.064***	0.064***	0.071***	0.070***
	(0.016)	(0.015)	(0.015)	(0.015)
Period <sup>2</sup>	- 0.002***	- 0.002***	- 0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Cognitive score		2.206***	2.203***	2.206***
		(0.620)	(0.619)	(0.619)
Female		-0.746***	-0.745***	-0.744***
		(0.218)	(0.217)	(0.217)
Economics/Business		0.084	0.083	0.083
		(0.260)	(0.260)	(0.260)
English		-0.002	0.007	0.008
		(0.226)	(0.226)	(0.226)
Position			-0.051***	-0.052***
			(0.011)	(0.012)
Positive			0.401***	0.408***
			(0.079)	(0.080)
Attribute complexity				-0.070
				(0.071)
Option complexity				-0.052
				(0.069)
Observations	8555	8555	8555	8555
Session FE	Yes	Yes	Yes	Yes

Iddle o Raik icgicssions	Table 6	Rank	regressions
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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

p < 0.10, p < 0.05, p < 0.01

A comparison of these results suggests that it is worthwhile to investigate the effects of Time spent in a decision problem on the Mistake Rate. Table 8 displays results from logistic regressions used to explicitly test for the effect of additional time spent in the decision problem on the mistake rate and how this effect differs by decision problem type. Model 1 is conducted for the sub-sample excluding decision problems of type  $O_{15}A_{15}$  and shows that increased time spent does not

	(1)	(2)	(3)	(4)	(5)	(6)
	Time	Time	Time	Time	Time <sup>a</sup>	Time <sup>b</sup>
Options	2.215***	2.217***	1.136**	- 1.669*	- 1.121	- 1.470
	(0.381)	(0.380)	(0.465)	(0.949)	(0.965)	(0.906)
Attributes	5.655***	5.649***	5.367***	4.922***	5.083***	4.629***
	(0.430)	(0.430)	(0.438)	(0.932)	(1.084)	(0.885)
Options * Attributes	1.734***	1.729***	1.991***	2.112***	3.481***	1.956***
	(0.499)	(0.499)	(0.500)	(0.503)	(0.532)	(0.486)
Period	-0.394***	-0.395***	-0.412***	-0.403***	- 0.190***	- 0.350***
	(0.078)	(0.078)	(0.079)	(0.079)	(0.067)	(0.074)
Period <sup>2</sup>	0.002	0.002	0.003	0.003	-0.000	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cognitive score		9.054**	9.052**	9.053**	6.520**	9.141**
		(4.251)	(4.251)	(4.252)	(3.277)	(4.158)
Female		-2.377*	-2.378*	-2.378*	- 1.540	- 2.398*
		(1.354)	(1.354)	(1.354)	(1.124)	(1.325)
Economics/Business		- 1.739	- 1.740	- 1.741	- 2.620*	- 1.860
		(1.601)	(1.601)	(1.601)	(1.378)	(1.563)
English		-3.451**	-3.452**	- 3.452**	- 2.076	- 3.295**
		(1.496)	(1.496)	(1.496)	(1.357)	(1.462)
Position			0.146***	0.184***	0.191***	0.172***
			(0.040)	(0.042)	(0.045)	(0.041)
Positive			- 1.257***	- 1.443***	- 1.068***	- 1.430***
			(0.274)	(0.279)	(0.275)	(0.269)
Attribute complexity				0.118	- 0.031	0.148
				(0.228)	(0.292)	(0.215)
Option complexity				0.774***	0.588**	0.727***
				(0.223)	(0.233)	(0.211)
Observations	8880	8880	8880	8880	6668	8880
Session FE	Yes	Yes	Yes	Yes	Yes	Yes

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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

<sup>a</sup>Conditional on correct

<sup>b</sup>: Timeouts treated as Time = 75 s

decrease the mistake rate. Model 2 is conducted for the sub-sample excluding decision problems of type  $O_5A_5$  and shows that increased time spent does decrease the mistake rate in the presence of additional irrelevant information—so long as irrelevant information was already present. For example, the coefficient on Time

	(1)	(2)
	Mistake	Mistake
Options	0.003	0.171***
	(0.050)	(0.053)
Attributes	0.062	0.241***
	(0.052)	(0.056)
Period	- 0.007***	- 0.006***
	(0.002)	(0.002)
Period <sup>2</sup>	0.0002***	0.0001***
	(0.000)	(0.000)
Time	- 0.001	0.002
	(0.001)	(0.001)
Time * Attributes	- 0.000	-0.003***
	(0.001)	(0.001)
Time * Options	- 0.000	-0.002***
	(0.001)	(0.001)
Position	0.004***	0.006***
	(0.002)	(0.001)
Positive	- 0.040***	-0.035***
	(0.009)	(0.009)
Attribute complexity	-0.014	0.003
	(0.010)	(0.008)
Option complexity	- 0.006	0.011
	(0.009)	(0.007)
Observations	6460	6393
Session FE	Yes	Yes
Demographics	Yes	Yes
Sample	$O_5A_5, O_5A_{15}, O_{15}A_5$	$O_5A_{15}, O_{15}A_5, O_{15}A_{15}$

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 Table 8
 Effect of time spent on mistake rate

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

\* Attributes in model 2 tells us that an additional second spent in a decision problem of type  $O_{15}A_{15}$  reduces the mistake rate by 0.3 percentage points relative to an additional second spent in  $O_{15}A_5$ . In each model, we test whether the coefficients on Time \* Attributes and Time \* Options are different from one another and fail to reject the null in each instance (p > 0.1 in both tests), indicating that additional Options and Attributes have symmetric effects on the effectiveness of time on the mistake rate.

Taken together, the results in Tables 3 and 8 illuminate a possible mechanism through which we see our results. In general, subjects do spend more time on

decision problems with irrelevant information. This additional time spent does not, however, "pay off" by decreasing the mistake rate when irrelevant information is presented in only one dimension. However, conditional on irrelevant information being present in both dimensions, additional time spent does decrease the mistake rate, though not enough to undo the direct effect of the irrelevant information on the mistake rate, as evidenced by our results in Tables 2 and 4.

### 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, Fig. 2 reports that subjects are smoothly distributed in the support of the BDM range we provided. Such a smooth distribution is also observed when we look at the WTP data for Low and High Noise environments separately.

Table 9 shows the average WTP, measured in ECUs, for each type of elimination. Table 9 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 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  $H_0$ :  $WTP(A | O_5) = WTP(O | A_5)$ ).

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 dimensions. Subjects do not seem to anticipate this effect on mistake rates when setting their WTP. Additionally, Table 10 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.



#### Table 9 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
Ν	112	112	110	110

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

p > 0.100 otherwise

#### Table 10 WTP greater than zero

	Low noise		High noise	
	$WTP(A O_5)$	$WTP(O A_5)$	$\overline{WTP(A O_{15})}$	$WTP(O A_{15})$
Mean	0.893	0.866	0.864	0.882
Std error	0.029	0.032	0.033	0.031
Ν	112	112	110	110

p > 0.100 in all relevant comparisons

Average WTP for any case in Table 9 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 Sect. 3.3: a "preference for simplicity."

The regressions reported in Table 11 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 11 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  $WTP(O|A_n)$ .<sup>22</sup> 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 11 are straightforward.<sup>23</sup>

First we ask if WTP to eliminate irrelevant information in either dimension is sensitive to measures of performance in Part 1 of the experiment, despite there being

 $<sup>^{22}</sup>$  For these regressions, answers submitted at *time* = 75 s are coded as mistakes to avoid collinearity of regressors.

 $<sup>^{23}</sup>$  Table 24 of Electronic supplementary material Appendix B.3 repeats the regressions reported in Table 11 by replacing the measure for Cognitive Score with self-reported GPA. The results are qualitatively the same.

	(1) WTP	(2) WTP	(3) WTP	(4) WTP > 0	(5) $WTP > 0$	(6) WTP > 0
	W 11	W 11	W 11	w II > 0	w II > 0	w II > 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

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

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 s 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 11. 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 11; 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 9 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 11 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:

#### **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 11, 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 12 and 13 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 different stakes 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 12 and 13 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.<sup>24</sup>

We present the summary statistics of WTP in Table 12 and the frequency of positive WTP amount in Table 13. 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 12, 13 and 9, 10 reveals that the mean WTP and frequency of positive WTP closely matches that of the overall sample. In Tables 12 and 13, we can reject a null hypothesis  $H_0$ :  $\mu_{No Additional Mistakes (or Time Costs)} = \mu_{Additional Mistakes (or Time Costs)}$  in a Mann-Whitney test in each of the 16 instances. For example, in Table 12 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  $\alpha$  level. Note that in no instance in Tables 12 and 13 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).

<sup>&</sup>lt;sup>24</sup> 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 may appear in some cells of Tables 12 and 13, but not all. These measures do not require any joint conditions over multiple decision problem types for a given subject.

	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	4.130	4.031	4.192	4.146
time costs	(.388)	(.338)	(.517)	(.396)
	54	65	26	41

Table 12 WTP: no additional mistakes

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

Low noise High noise  $WTP(O|A_5)$  $WTP(A|O_{15})$  $WTP(O|A_{15})$  $WTP(A|O_5)$ No additional mistakes 0.919 0.868 0.837 0.844 (0.035)(0.041)(0.057)(0.055)45 62 68 43 No additional mistakes or 0.907 0.862 0.885 0.854 time costs (0.040)(0.043)(0.064)(0.056)54 65 26 41

Table 13 Frequency of positive WTP: no additional mistakes

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

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  $H_0$ :  $F(y_{additional mistakes}(I|J_k)) = F(y_{no additional mistakes}(I|J_k))$  for each  $(I, J_k)$ . Such tests also fail to reject the analogous null for WTP levels themselves  $(H_0 : F(WTP_{additional mistakes}(I|J_k)) = F(WTP_{no additional mistakes}(I|J_k)))$ .

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 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.

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 14:

In the treatments designated as " $8 \times 8$ " 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 Electronic supplementary material Appendix D. In this section, we will highlight several important results that further illuminate the main contributions of this paper. In Sect. 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 15.

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  $8 \times 8$  design, we can more precisely investigate the effect of the "size" of the irrelevant information set on mistake rates. The  $8 \times 8$  design leads to the counts of irrelevant cells of information as described by Table 16. 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.<sup>25</sup>

Table 28 in Electronic supplementary material Appendix D.1 reports mistake rates across all decision problem types in the  $8 \times 8$  treatments. The main messages of Tables 28 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.<sup>26</sup> The results in Table 28 are robust to the exclusion of timeouts, reported in Table 29. 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.

<sup>&</sup>lt;sup>25</sup> 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 when presented alone. 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 there is sufficient evidence that, within the confines of our experimental design, the interaction between unavailable options and irrelevant attributes indeed matters.

<sup>&</sup>lt;sup>26</sup> 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. Nevertheless it is important to note that even the lower bound of the mistake rate in  $O_8A_8$  is higher than those observed in  $O_5A_{15}$  and  $O_{15}A_5$ .

Table 11 Robustiess treatment summary				
Treatment	# of Sessions	# of Subjects	Part 1: Decisions	Part 2: BDM
$8 \times 8$ : Low noise	2	32	40 Decisions	$O_8A_5 \rightarrow O_5A_5$ and $O_5A_8 \rightarrow O_5A_5$
$8 \times 8$ : 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	$O_{15}A_{15} \rightarrow O_5A_5$

Table 1/ Poblistness treatment summary

Table 15         Treatments and           irrelevant information	Treatment	Irrelevant cells
	$O_5A_5$	0
	$O_5 A_{15}$	50
	$O_{15}A_5$	50
	$O_{15}A_{15}$	200

<b>Table 16</b> Robustness treatmentsand irrelevant information	Treatment	Irrelevant cells
	$O_{5}A_{5}$	0
	$O_{5}A_{8}$	15
	$O_{8}A_{5}$	15
	<i>O</i> <sub>8</sub> <i>A</i> <sub>8</sub>	39

Additionally, Electronic supplementary material Appendix D.1 reports average Time spent in decision problems in the 8x8 treatments in Tables 30 through 32. 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 33 reports the incidence of Timeouts for the  $8 \times 8$  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  $8 \times 8$  treatments are similar to our results for WTP in the main experiments, where we observe positive WTP to eliminate irrelevant information (see Tables 34 and 35 in Electronic supplementary material Appendix D.2). One thing worth noting here is that the average WTP is much lower in control experiments (Tables 34 vs 9) and that subjects less frequently submit positive WTP amounts in control experiments than main experiments (Tables 35 vs 10). 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 ( $O_{15}A_{15} \rightarrow O_5A_{15}$ ,  $O_{15}A_{15} \rightarrow O_{15}A_5$ , and  $O_{15}A_{15} \rightarrow O_5A_5$ ) in these sessions, the subject may be primed to internally rank these three WTPs with  $O_{15}A_{15} \rightarrow O_5A_5$  as the "most valuable" simply due to the relatively large number of irrelevant cells eliminated. To avoid this priming, we ask for WTP for  $O_{15}A_{15} \rightarrow O_5A_5$  alone.

We find results consistent with our hypothesis, as indicated in Tables 36 and 37 in Electronic supplementary material Appendix D.3. Mean WTP for  $O_{15}A_{15} \rightarrow O_5A_5$ 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  $O_{15}A_{15} \rightarrow O_5A_5$ , very similar to the frequency of positive WTP reported in Table 10. Hence, subjects report positive WTP for  $O_{15}A_{15} \rightarrow O_5A_5$  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

In this project, we set out to understand whether irrelevant information could ever be relevant in a given decision problem. Our results show that it is: unavailable options and irrelevant attributes can affect the optimality of choice. In this section we discuss some of the reasons behind our experimental design, the implications of our results, and the external relevance of this study.

We mentioned previously that screen size limitations prevent us from exploring the effects of the addition of more than ten unavailable options or irrelevant attributes. Adding any more information in either dimension would necessitate the use of filters, scrolling, text size changes across decision problems, etc., all of which would present confounds to our experimental design. We therefore cannot rule out that it is possible that there is free disposal of irrelevant information in a single dimension *up to a certain threshold*, beyond which one might observe effects on choice. It is easy to imagine examples where this mechanism can be reasonably assumed; adding a single out-of-stock TV to the in-store display of 10 available TVs at Costco likely has no effect on choice, but adding 50 might. If we take this threshold mechanism as given, one can then interpret our results in the following fashion: even when the addition of irrelevant information in a single dimension is not sufficient to affect choice, adding *both* unavailable options and irrelevant attributes in amounts lower than this threshold can affect choice. Moreover, even if this threshold-based mechanism were true, the threshold of information in one dimension required to affect choice is likely context-dependent, such that estimating such a threshold in a laboratory environment is likely not very generalizable. Nevertheless, we view further investigation of the characteristics of the mistake rate function as worthwhile for future research.

Our design is not crafted to figure out the exact functional form of the cost of processing different types of irrelevant information. Nevertheless, our findings indicate that even when each type of irrelevant information is within manageable range of processing cost, the subjects may start making more mistakes when they are jointly processed. We argue that this might be either due to the excess number of additional cells the subject processes when both types of irrelevant information are added or due to mentioned complementarities. Our 8x8 design is helpful to understand the role of the first effect. Note that in  $O_8A_8$ , the number of cells of irrelevant information presented in two dimensions is still less than the number of irrelevant cells in  $O_5A_{15}$  or  $O_{15}A_5$  (39 vs 50). Finding higher mistake rates in  $O_8A_8$  than  $O_5A_{15}$  or  $O_{15}A_5$ is interpreted as evidence that it is not just the absolute number of cells that needs to be ignored determining the mistake rates, but also the interaction between the two dimensions. Note also that due to the differential difficulty levels of the two treatments and potential heterogeneity of subjects, one would expect lower mistake rates in  $O_8A_8$ . However, even with such bias we observed a higher mistake rate in  $O_8A_8$ than in  $O_5A_{15}$ .

We view our results as being particularly relevant for issues of information disclosure. For example, there is some debate in the United States as to whether to require food manufacturers to disclose whether their products use genetically modified organisms (GMOs). In the absence of meaningful evidence of the negative health consequences of GMOs, the decision of whether to require such disclosure comes down to a discussion of consumer preferences. The logic might be that some consumers strictly prefer to consume only non-GMO products and so deserve to have access to this (relevant) information. Of course, some consumers have no such preference and, for them, the issue of whether GMOs are included in their food is irrelevant. Prior to gaining the knowledge contained in this project, it could reasonably be assumed that these consumers could simply freely dispose of this irrelevant GMO information when evaluating goods and so requiring disclosure should not impose any new costs on these consumers. However, we show that in some contexts it is possible that such irrelevant information can make people worse at making decisions. Moreover, even when someone does not make additional mistakes in the presence of irrelevant information, our willingness to pay results and the observed preferences for simplicity indicate that their welfare may be negatively affected directly by the inclusion of this information. All this is to say that our results would suggest a new trade-off that would need to be considered by policy makers in this GMO example; policy makers would now have to weigh the potential benefit of information disclosure to consumers who care about GMOs against the newly identified cost imposed by this irrelevant information on consumers who do not. Developing tools that allow consumers to filter the information they prefer to receive and allowing them sorting options based on their availability should be feasible at online shopping platforms.

### 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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