Judgments of length in the economics laboratory: Are there brains in choice?*

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Abstract

We design a choice experiment where the objects are valued according to only a single attribute with a continuous measure and we can observe the true preferences of subjects. However, subjects have an imperfect perception of their own preferences. Subjects are given a choice set involving several lines of various lengths and are told to select one of them. They strive to select the longest line because they are paid an amount that is increasing in the length of their selection. Subjects also make their choices while they are required to remember either a 6-digit number (high cognitive load) or a 1-digit number (low cognitive load). We find that subjects in the high load treatment make inferior line selections and perform worse searches. When we restrict attention to the set of viewed lines, we find evidence that subjects in the high load treatment make worse choices than subjects in the low load treatment. Therefore the low quality searches do not fully explain the low quality choices. Our results suggest that cognition affects choice, even in our idealized choice setting. We also find evidence of choice overload even when the choice set is small and the objects are simple. Further, our experimental design permits a multinomial discrete choice analysis on choice among single-attribute objects with an objective value. The results of our analysis suggest that the errors in our data are better described as having a Gumbel distribution rather than a normal distribution. Finally, we observe the effects of limited cognition, consistent with memory decay and attention.

Keywords: cognitive load, choice, choice overload, judgment, memory, search

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1 Introduction

Consider a subject making a binary choice between a bag of potato chips and a can of soda. The choice from this relatively unhealthy set would allow the experimenter to conduct an inference of the preferences of the subject. However, this inference is noisy and it is not straightforward to detect a suboptimal choice.

If preferences are also elicited by a supplementary method (for example, eliciting either willingness to pay or a ranking of the objects) the experimenter could compare the choice with this alternate measure. However, both the choice and the supplementary elicitation are noisy. In the case that preferences are not elicited by a different method, the experimenter would only be able to identify that a suboptimal action was taken when intransitive choices were made. In contrast to these two cases, we design an experiment where we have a perfect measure of the preferences of subjects and we are therefore able to determine-without noise-whether subjects selected a suboptimal action.

After the chips-soda choice, suppose that the subject is to make another choice from a different set and the subject will only be given one of their two choices. This second binary choice is between a can of orange soda and a glass of orange juice. Given an isolated choice between these objects, the subject would prefer the orange soda. However, after the unhealthy first choice, the subject selects the orange juice. More generally, due to the repeated nature of a choice experiment, the attributes of items in previous decision sets might interact with subsequent decisions in a manner that is not discernible to the observer.

We design a choice experiment where the objects in our experiment are valued according to only a single attribute and we can observe the true preferences of the subject. Further, since the objects only have one objective value according to a single dimension, there will not be an undetected relationship between one of several attributes from a previous choice and one of several attributes of a subsequent choice.

The objects of choice are lines that vary in length. Subjects attempt to select the longest line because they are paid an amount that is increasing in the length of their selection. While we are able to observe the true objective length of each line, it is well-known that subjects have imperfect perception of objectively measurable objects (Weber, 1834; Fechner, 1860; Thurstone, 1927a,b). In other words, even where objects have objectively measurable properties, perception of them is imperfect.

Certain regularities regarding these imperfect perceptions have been known for some time. Perhaps the oldest such regularity is that the larger the stimuli, the more difficult it is to detect absolute differences between stimuli (Fechner, 1860). For instance, it is often more difficult to determine the heaviest between a 5kg weight and a 5.5kg weight than it is to determine the heaviest between a 1kg weight and a 1.5 kg weight. This regularity is sometimes referred to as Weber's Law.

Further, the imperfect perception of objective quantities has led researchers to consider that one's preferences might be imperfectly perceived and this has served as a justification for random choice or random utility models. For instance, Bradley and Terry (1952), Luce (1959a,b), Becker, DeGroot, and Marschak (1963), McFadden (1974, 1976, 1981, 2001), Yellott (1977), and Falmagne (1978) each make explicit reference to Weber, Fechner, or Thurstone.[1] However, despite this known connection between imperfect perception of objective properties and stochastic choice, to our knowledge, we are the first to conduct an experiment where suboptimal choices are perfectly observable because utility is represented by a static, single-attribute physical quantity with an uncountable measure.

Subjects are given a choice set involving several lines of various lengths and are directed to select one of them. Subjects can only view one line at a time. This design simulates the feature that deliberation about the desirability of an object compared to another object crucially involves the memory of the assessments of the objects. This design also allows us to observe the search history of subjects.

Subjects make their choice when under a cognitive load. This experimental manipulation is designed to affect the available cognitive resources of subjects, so that the relationship

[1] More recent papers that cite these authors include Luce (1994, 2005), Ballinger and Wilcox (1997), Loomis, Peterson, Champ, Brown, and Lucero (1998), Butler (2000), Butler and Loomes (2007), Blavatskyy (2008, 2011), Rieskamp (2008), Caplin (2012), Lévy-Garboua, Maafi, Masclet, and Terracol (2012), Fudenberg, Iijima, and Strzalecki (2015), Agranov and Ortoleva (2017), Argenziano and Gilboa (2017), Khaw, Li, and Woodford (2017), Alós-Ferrer, Fehr, and Netzer (2018), Caplin, Csaba, and Leahy (2018), Navarro-Martinez, Loomes, Isoni, Butler, and Alaoui (2018), and Olschewski, Newell, and Scheibehenne (2019).

between cognition and behavior can be observed.[2] Some choices are made when required to remember a 6-digit number (high cognitive load) and others when required to remember a 1-digit number (low cognitive load). We have observations about the searches and the choices of subjects in both cognitive load treatments.

We find that subjects in the high load treatment make inferior line selections. In particular, the longest line is less likely to be selected and the difference between the length of the longest line and length of the selected line is larger in the high load treatment. We also find that subjects in the high load treatment conduct worse searches in that they have fewer unique line views, fewer overall line views, and they spend less time viewing the longest line. When we restrict attention to the set of viewed lines, we still find evidence that subjects in the high load treatment make worse choices than subjects in the low load treatment. Our results suggest that, even in our idealized setting, choice is affected by the availability of cognitive resources. We also find evidence of choice overload in a setting without complicated objects (our objects are simply line lengths) or without many objects (our largest choice set has 6 items). Further, our design permits a multinomial discrete choice analysis (McFadden, 1974) on choice among single-attribute objects with an objective value. The results of our analysis suggest that the errors in our data are better described as having a Gumbel distribution rather than a normal distribution. Finally, we observe the effects of limited cognition, consistent with memory decay and attention.

2 Related literature

In order to make sense of choice data, researchers have advanced random utility or random choice models. The classic efforts include Bradley and Terry (1952), Debreu (1958), Luce (1959a,b), and Becker, DeGroot, and Marschak (1963). Numerous other random utility or random choice experimental and theoretical papers have emerged in an effort to better un-

[2] For instance, see Duffy and Smith (2014) and Deck and Jahedi (2015).

derstand choice.[3,4] The conceptualization that utility is random has also lead to significant advances in econometrics (McFadden, 1974, 1976, 1981, 2001).

We are not the first authors to study choice in a setting where outcomes depend on an imperfectly perceived object. For instance, Caplin and Dean (2015) and Dutilh and Rieskamp (2016) examine choice when the judgments involve imperfectly perceived static objects. Zeigenfuse, Pleskac, and Liu (2014) examine choice involving judgments of imperfectly perceived dynamic objects. These papers are different from ours in many respects, perhaps most notably because the imperfect perception in these settings could (in principle) be eliminated by carefully counting the discrete and finite measures. By contrast, the measure of line length is not countable and therefore the imperfect perception is more difficult to eliminate.

To our knowledge, there are only two instances of papers that study choice where outcomes depend on an imperfectly perceived object with an uncountable measure. However, both differ from our setting. Tsetsos, Moran, Moreland, Chater, Usher, and Summerfield (2016) study choice that involves judgements of the heights of bars. Such a measure is uncountable, however the size of the bars within each trial is dynamic: the subjects are charged with estimating the distribution within a trial. By contrast, the size of each line in our setting is static within each trial. Polanía, Krajbich, Grueschow, and Ruff (2014) examine choice in a setting where outcomes are based on the area occupied by the image of various objects. Area is also an uncountable measure. However, the images have different shapes and so the objects vary according to several meaningful attributes. Therefore, to our knowledge, we are the first to study choice in a setting where outcomes depend on imperfectly perceived static objects with an uncountable measure that varies only according to a single relevant attribute.

Some of the recent choice literature has focused on consideration set effects, whereby

[3] A partial list of these efforts, not previously mentioned, would include Tversky (1969), Loomes, Starmer, and Sugden (1989), Sopher and Gigliotti (1993), Loomes and Sugden (1995), Sopher and Narramore (2000), Gul and Pesendorfer (2006), Rubinstein and Salant (2006), Tyson (2008), Caplin, Dean, and Martin (2011), Conte, Hey, and Moffatt (2011), Wilcox (2011), Gul, Natenzon, and Pesendorfer (2014), Loomes and Pogrebna (2014), Woodford (2014), Caplin and Dean (2015), Caplin and Martin (2015), Cubitt, Navarro-Martinez, and Starmer (2015), Lu (2016), Apesteguia, Ballester, and Lu (2017), Dean and Neligh (2017), Ahumada and Ulku (2018), Apesteguia and Ballester (2018), Echenique, Saito, and Tserenjigmid (2018), Koida (2018), Kovach and Tserenjigmid (2018), Caplin, Dean, and Leahy (2019), Conte and Hey (2019), and Natenzon (2019).

[4] For a partial list from the psychology literature, see Regenwetter, Dana and Davis-Stober (2011), Regenwetter, Dana, Davis-Stober, and Guo (2011), Regenwetter and Davis-Stober (2012), Birnbaum and Schmidt (2008, 2011), and Birnbaum (2011).

the decision maker does not consider the entire set of objects and this is not necessarily observable to the experimenter.[5] However, with our experimental design, we can observe the consideration set and the objective lengths of the lines. We find that the longest viewed line is not selected in many trials and this selection is affected by available cognitive resources. We also find evidence that subjects in the high load treatment make worse choices than subjects in the low load treatment, even when we restrict attention to the set of viewed lines. Our analysis therefore suggests that, while there are possibly also consideration set effects, imperfect perception about one's preferences is a key component to understanding stochastic choice.

Matějka and McKay (2015) offer a rational inattention foundation for discrete choice models. Agents optimally allocate costly attention in order to better understand the true state of nature.[6] Specifically, the agents can reduce the Shannon entropy associated with the choice setting by incurring costs associated with attention. The authors show that this implies a random choice specification similar to Luce (1959a). In our experiment, there is a similar process as subjects devote cognitive effort in order to select the longest line in the choice set.

Reutskaja, Nagel, Camerer, and Rangel (2011) report on a choice experiment that employs eye tracking equipment. Subjects select items under time pressure (3 seconds) from choice sets of 4, 9, and 16 objects. Prior to the choice, the experimenters elicit valuations of the objects. This alternate elicitation allows the authors to judge the quality of the choices. The authors find that the quality of choices among the set of viewed objects decreased in the size of the choice set. The authors also find that the quality of searches decreased in the size of the choice set. Additionally, the authors report that the spatial location of the object is related to choice and that there is evidence that subjects exhibit memory decay of the value or the location of the viewed object. Our experiment has a different design, as our subjects have, for instance, 15 seconds to select among $2-6$ single-attribute objects. Most notably though, we can objectively determine the quality of the choice since we know the exact lengths of the lines. Despite these design differences, we find many parallel results. For instance, we find

[5] For instance, see Masatlioglu, Nakajima, and Ozbay (2012), Manzini and Mariotti (2014), Aguiar, Boccardi, and Dean (2016), Cattaneo, Ma, Masatlioglu, and Suleymanov (2017).

[6] Also see Weibull, Mattsson, and Voorneveld (2007).

that the quality of the choice decreases in the size of the choice set and we observe outcomes consistent with memory decay.

There is a large literature that employs the cognitive load manipulation in order to affect the available cognitive resources of subjects. Although much of this research appears in the psychology literature, the technique is more frequently appearing in the economics literature,[7] including in strategic settings.[8] Most relevant to our purposes, research finds that subjects in a high cognitive load treatment fail to process available and relevant information (Gilbert, Pelham, and Krull, 1988; Swann, Hixon, Stein-Seroussi, and Gilbert, 1990). We also note that subjects under a cognitive load tend to perform worse on visual judgment tasks (Morey and Cowan, 2004; Allen, Baddeley, and Hitch, 2006; Cocchi et al., 2011; Morey and Bieler, 2013; Zokaei, Heider, and Husain, 2014; Allred, Crawford, Duffy, and Smith, 2016).

To our knowledge, there are only two other examples of papers that employ the cognitive load manipulation in a choice setting: Lee, Amir, and Ariely (2009) and Drichoutis and Nayga (2018).

Lee, Amir, and Ariely (2009) study intransitive choices among pair-wise decisions made while their subjects are under a cognitive load.[9] Surprisingly, the authors find that subjects under a high cognitive load make fewer intransitive choices than subjects under a low cognitive load. However, these are real world objects that have attributes whose desirability is not observable to the experimenters. Further, the repeated nature of the experiment makes it difficult to determine if the attributes from previous choices affected subsequent choices (either because the attributes are regarded as complements or substitutes). By contrast our subjects make judgments on objects that have a value based on single objective attribute.

Drichoutis and Nayga (2018) find that a high cognitive load does not increase internal inconsistency on a GARP budget allocation task. By contrast, we find that the cognitive load manipulation negatively affects choices and searches.

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[7] For instance, see Benjamin, Brown, and Shapiro (2013), Schulz, Fischbacher, Thöni, and Utikal (2014), Deck and Jahedi (2015), and Hauge et al. (2016).

[8] See Milinski and Wedekind (1998), Roch et al. (2000), Cappelletti, Güth, and Ploner (2011), Carpenter, Graham, and Wolf (2013), Duffy and Smith (2014), Allred, Duffy, and Smith (2016), Buckert, Oechssler, and Schwieren (2017), and Duffy, Naddeo, Owens, and Smith (2019).

[9] See Experiment 4.

Our experiment presents subjects with a decision problem with an objectively optimal solution. However because of imperfections with the subjects, they are not able to attain the optimal solution with certainty. This feature also appears in Gabaix et al. (2006) and Sanjurjo (2015, 2017). There subjects are given a multi-attribute choice problem where each attribute value is represented by a number. Since subjects cannot fully process the available information, despite that there is an objectively optimal solution, the optimal solution is not attained with certainty. Also similar to our setting, subjects must click on the information in order to make it appear. In this way, similar to this multi-attribute literature, we can observe the process of search.[10]

3 Experimental design

3.1 Overview

The experiment was programmed on E-Prime 2.0 software (Psychology Software Tools, Pittsburgh, PA). The sessions were performed on standard 23 inch (58.42 cm) Dell Optiplex 9030 AIO monitors. E-Prime imposed a resolution of 1024 pixels by 768 pixels. A total of 92 subjects participated in the experiment.

3.2 Line selection task

In each round, subjects were presented a choice set of lines that ranged in number between 2 and 6. Each of these choice set sizes occurred with probability $\frac{1}{5}$ and were drawn with replacement. Subjects were able to only view one line at a time. The lines were labeled in alphabetic order at the bottom of the screen. Letters A and B always represented the first two options, and consecutive letters were added as needed. Subjects could view a particular line by clicking on the letter label that corresponds to that particular line. A click on a particular letter label would reveal the corresponding line. To view another line, subjects click on its corresponding label. This makes the new line appear and the old line disappear.

[10] Also see Payne, Braunstein, and Carroll (1978) and Payne, Bettman, and Johnson (1993).

Each line appeared within a rectangular region of 400 pixels in the horizontal direction and 150 pixels in the vertical direction. The boundaries of these regions were not visible to the subjects. The lines were randomly offset vertically and horizontally within these regions such that there was a minimum cushion between the line and the edge of the region. This cushion was 20 pixels in the horizontal direction and 10 pixels in the vertical direction. The offsetting was fixed for each line throughout each trial. The regions were non-overlapping and arranged in 2 columns and 3 rows, with the regions for A and B in the top row, the regions for C and D in the middle row, and the regions for E and F in the bottom row.

The length of the lines in any trial were determined by subtracting various amounts from the *longest line*. There were 10 possible longest line lengths in pixels ranging in 16 pixel (0.80 cm) increments from 160 pixels (8.0 cm) to 304 pixels (15.1 cm). The lines each had a height of 0.38 cm.

There were three line length treatments. In the *difficult* treatment, one line was exactly one pixel shorter than the longest, and the other differences were drawn from a uniform on $\{-1, ..., -11\}$. In the *medium* treatment, one line was exactly 12 pixels shorter than the longest and the other differences were drawn from a uniform on $\{-12, ..., -39\}$. In the *easy* treatment, one line was exactly 40 pixels shorter than the longest, and the other differences were drawn from a uniform on $\{-40, ..., -100\}$. The difficult, medium, and easy treatments each occurred with probability $\frac{1}{3}$, in random order, and are drawn with replacement. The subjects were not informed of the existence of these treatments.

Below each letter label was a box indicating that the subject currently *selected* that line. Subjects could change this selection at any time during the allotted 15 seconds. The subjects could view the time remaining, rounded to the nearest second. See Figure 1 for a screenshot[11] and Figure 2 for a characterization of the regions, which are not visible to the subjects.

[11] See https://osf.io/srpzh/ for the full set of screenshots.

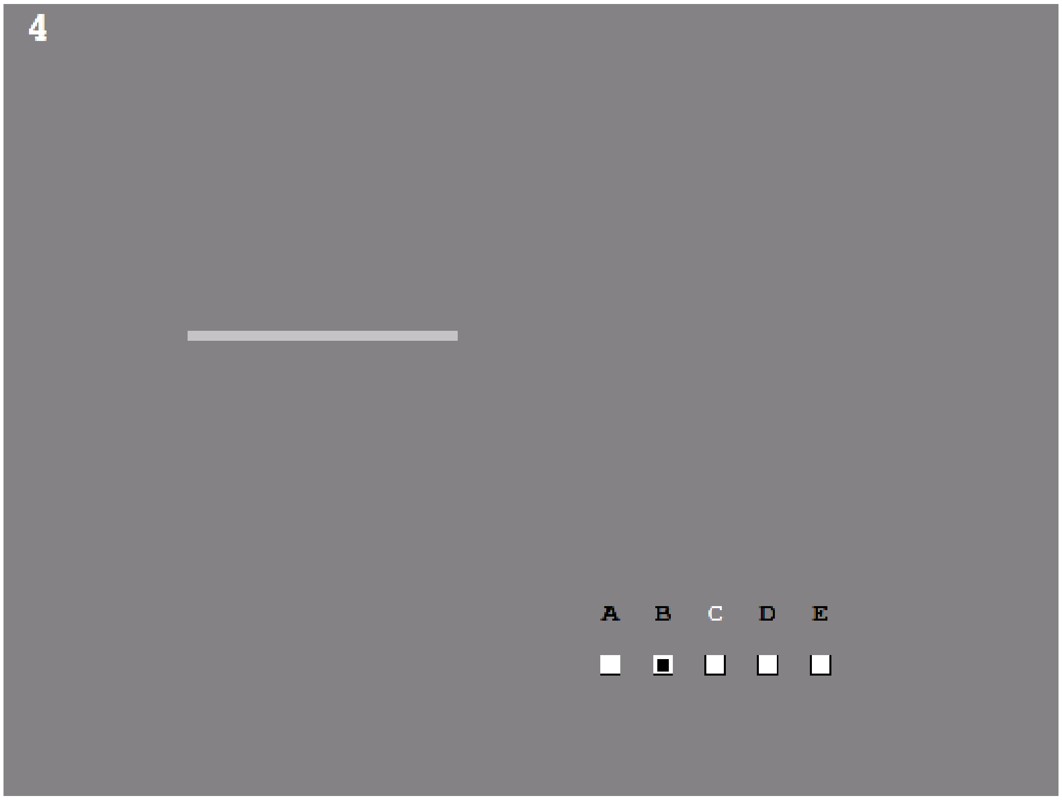

Figure 1: Screenshot from a trial with 5 lines in the choice set, where line C is being viewed, line B is currently selected as the longest, and there are 4 seconds remaining.

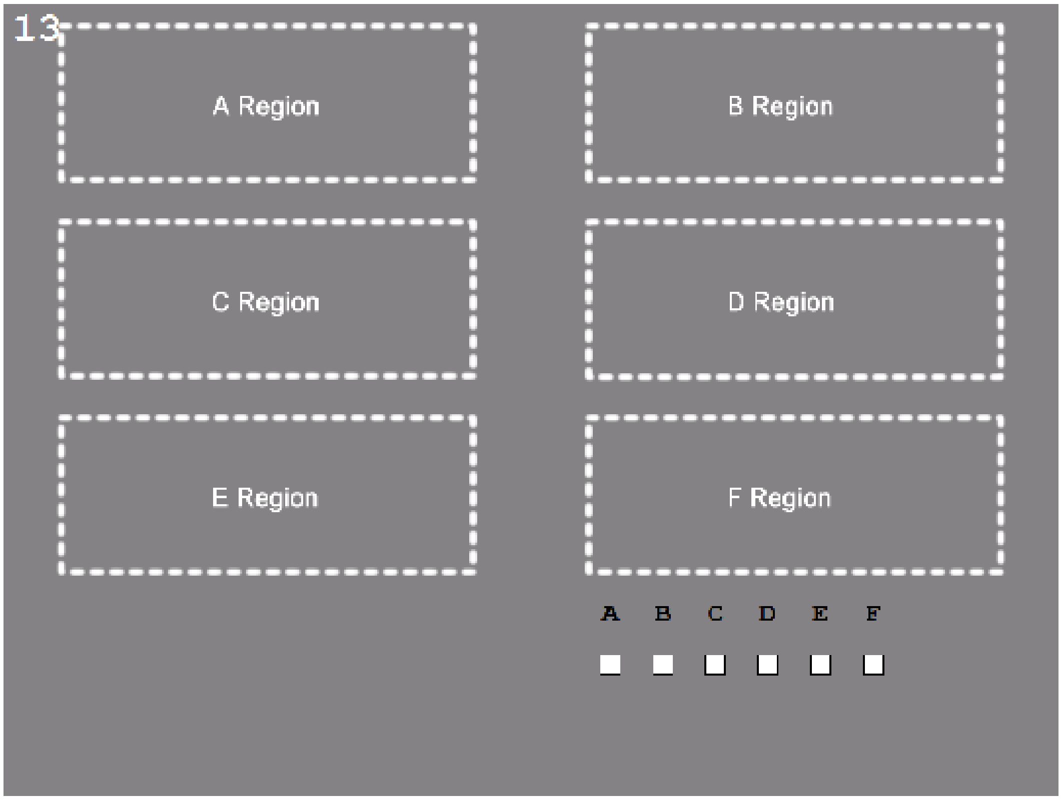

Figure 2: A characterization of the regions, invisible to the subjects, which contain the corresponding lines.

The choice within each trial was the line that was selected when the 15 seconds expired. If the subjects did not select a line before time expired, it was assumed that the selected line had a length of 0. Regardless of their actions in the line judgment screen, subjects would only advance to the following screen when the 15 seconds had expired. The earnings for this task were increasing in the length of the choice in that trial, at a rate of $1 per 240 pixels (or $0.4167 per 100 pixels).

3.3 Cognitive load treatments

There were 50 trials where subjects were given a 6-digit number to remember, which we refer to as *high load*. There were 50 trials where subjects were given a 1-digit number to remember, which we refer to as *low load*. These were given in random order. Regardless of the load, subjects were given 5 seconds to commit the number to memory.[12] Subjects would only proceed to the following screen when the 5 seconds had expired. Each of the 10 longest line lengths were presented 5 times in the high load treatment and 5 times in the low load treatment, also in random order.

3.4 Unincentivized practice

Prior to the incentivized portion of the experiment, subjects had unincentivized practice remembering both a 1-digit and a 6-digit number. In contrast to the incentivized portion of the experiment, here subjects were told if their response was correct. If the response did not contain the correct number of digits then subjects were directed to repeat the practice memorization task.

Additionally, subjects had an unincentivized practice on the line selection task. Subjects were given this practice with a choice set of 5 lines in the medium difficulty treatment. If the subjects did not view any lines, did not select a line that they viewed, or did not select any lines, the subjects were informed of this and were directed to repeat the practice line selection task.

3.5 Payment details

Subjects completed 100 line selection tasks and 100 memorization tasks. Those who correctly completed all 100 memorization tasks were paid for 30 randomly determined line selections, those who correctly completed 99 were paid for 29, those who correctly completed 98 were paid for 28, and so on, until subjects who correctly completed 70 or fewer memorization tasks were not paid for any of the line selection tasks. In addition to these payments, subjects were also paid a $5 show-up fee. Subjects were paid in cash and amounts were rounded up to the nearest $0.25. Subjects earned a mean of $26.00.

[12] The subjects could not view the time remaining in this stage, as these numbers could interact with the memorization number.

3.6 Discussion of the design

The goals of our incentive scheme are as follows: strongly incentivize the memorization task, keep incentives for memorization in each period independent from incentives for the line selection task in that particular period, and maintain identical line selection incentives for high and low load memorization periods. To strive for these goals, we do not provide feedback on the memorization task and we pay a number of randomly selected line selection outcomes that is decreasing in the number of incorrect memorization tasks. Only 5 subjects out of 92 failed to correctly perform at least 70 memorization tasks, suggesting that the incentive scheme was sufficiently calibrated. In addition, as feedback was not given on the memorization task, it is not clear whether subjects realized that they were near or below 70 correct. Finally, while incorrectly answering a specific memorization task decreases incentives, this affects both high and low load trials equally and we are primarily interested in the difference between these treatments.

Subjects were given inflexible time constraints. These fixed times were given so that subjects were not able to strategically allocate their time in the experiment. For instance, this design would prohibit subjects in the high cognitive load treatment from spending less time in the line judgment task so that they could proceed quickly to the memorization task stage.

The boundaries of the regions that contained the lines were not visible to these visible to the subjects. Our concern was that any such aid would differentially benefit the judgment of the lengths of extreme (very short or very long) lines. Regions that contained a line always appeared in the identical spot for that trial. This was done in order to facilitate the location of the lines.

Finally, we do not put any constraints on the nature of the search beyond the time constraints and the constraint that only one line could be viewed at a time.

4 Results

4.1 Cognitive load

A larger fraction of memorization tasks were correctly completed under low load (97.6%, 4490 of 4600) than high load (85.8%, 3947 of 4600) according to a Mann-Whitney test, $Z = 20.53$, $p < 0.001$.

As each of the 92 subjects attempt 50 high load memorization tasks and 50 low load memorization tasks, Table 1 presents a characterization of the subject-level distribution of the number of correct memorization tasks by cognitive load treatment and the number pooled across treatments.

Table 1: Distribution of subjects by number of correct memorization tasks

	Restricted to cognitive load treatments							
	$46-50$	$41-45$	$36-40$	$31-35$	$26-30$	$21-25$	< 21	Total
High load	50	17	11	5	4	3	2	92
Low load	88	4	0	0	0	0	0	92

	Pooled across cognitive load treatments							
	$96-100$	$91-95$	$86-90$	$81-85$	$76-80$	$71-75$	< 71	Total
Pooled	40	24	13	4	5	1	5	92

The upper panel characterizes the subject-level distribution of the number of correct memorization tasks by cognitive load treatment. The lower panel characterizes the subject-level distribution of the correct memorization tasks across both cognitive load treatments.

Table 1 shows that 77 of the 92 subjects successfully completed more than 85% of their memorization tasks correctly. This suggests that the incentives were sufficient to elicit cognitive effort on these tasks.

4.2 Quality of choices

Here we explore the optimality of choices. We define the *Selected longest* variable to be a 1 if the choice was the longest available line and a 0 otherwise. Table 2 characterizes the Selected longest variable in the cognitive load and difficulty treatments.

Table 2: Selected longest variable by difficulty treatment

	Easy	Medium	Difficult	Pooled
High load	94.6%	73.1%	37.0%	68.9%
	1497 of 1582	1124 of 1538	548 of 1480	3169 of 4600
Low load	96.8%	76.3%	38.5%	69.6%
	1440 of 1487	1140 of 1495	623 of 1618	3203 of 4600
Pooled	95.7%	74.6%	37.8%	69.3%
	2937 of 3069	2264 of 3033	1171 of 3089	6372 of 9200

It appears to be the case that the difficulty treatments were successful in that the longest line is more likely to be selected in the easy treatment. Table 3 characterizes the variable by cognitive load and number of lines treatments.

Table 3: Selected longest variable by number of lines treatment

	2 Lines	3 Lines	4 Lines	5 Lines	6 Lines
High load	79.0%	74.0%	71.1%	62.3%	57.9%
	710 of 899	690 of 932	674 of 948	580 of 931	515 of 890
Low load	78.0%	75.0%	68.0%	66.4%	61.1%
	700 of 899	720 of 960	613 of 902	588 of 886	582 of 953
Pooled	78.4%	74.5%	69.6%	64.3%	59.5%
	1410 of 1798	1410 of 1892	1287 of 1850	1168 of 1817	1097 of 1843

It also appears that the probability that the longest line is selected is decreasing in the number of available lines. This appears to be suggestive of choice overload, even from a choice set of only a few simple objects of choice. Table 4 characterizes the variable in the cognitive load and longest line length treatments.

Table 4: Selected longest variable by longest line length treatment

	160	176	192	208	224	240	256	272	288	304
High load	71.1%	72.0%	69.1%	70.7%	70.4%	70.4%	66.7%	71.5%	64.4%	62.6%
Low load	71.7%	73.9%	75.0%	69.8%	69.4%	68.5%	66.3%	68.0%	67.6%	66.1%
Pooled	71.4%	72.9%	72.1%	70.2%	69.9%	69.5%	66.5%	69.8%	66.0%	64.3%

The Pooled values each have 920 observations. The values restricted to a cognitive load treatment each have 460 observations.

This suggests that the quality of choices decreases in the length of the longest line. In Table 5 we characterize the variable according to the number of lines and the letter label of the longest line.

Table 5: Selected longest variable by number of lines and letter label of the longest

	A	B	C	D	E	F
2 Lines	77.0%	79.9%	–	–	–	–
	705 of 916	705 of 882				
3 Lines	72.5%	72.5%	78.7%	–	–	–
	470 of 648	457 of 630	483 of 614			
4 Lines	64.8%	62.0%	71.6%	79.3%	–	–
	289 of 446	279 of 450	351 of 490	368 of 464		
5 Lines	64.1%	58.0%	62.8%	70.8%	66.0%	–
	236 of 368	215 of 371	219 of 349	250 of 353	248 of 376	
6 Lines	50.8%	52.8%	50.0%	60.2%	64.5%	78.7%
	167 of 329	161 of 305	144 of 288	197 of 327	180 of 279	248 of 315

There appear to be differences in accuracy conditional on the letter label of the longest line. Tables $2-5$ suggest the relevant variables that should be included in the analysis of the Selected longest line variable.

We now conduct regressions with the Selected longest variable as dependent variable. Since the dependent variable is binary, we employ a logistic specification. We include the High load variable, which obtains a 1 in the high load treatment, and a 0 otherwise. Further, since the Selected longest variable appears to be affected by the difficulty treatments, the number of lines treatments, the longest line treatments, and the letter that contained the longest line, we include these as independent variables. For the difficulty treatments, we include dummy variables indicating whether the treatment was Easy or whether the treatment was Difficult. To account for the letter label of the longest line, we offer specifications where we estimate a unique dummy variable for each of the 20 combinations of letter-number of lines as in Table 5. However, in the analysis immediately below we do not explore the effect of the letter label on the quality of the choice. We postpone our discussion of this issue until subsections 4.6 and 4.7. Due to the repeated nature of the observations, we also offer fixed-effects specifications where we estimate a dummy variable for each subject. We summarize these regressions in Table 6.

Table 6 Logistic regressions of the Selected longest line variable

	(1)	(2)	(3)	(4)
High load	-0.157^{**}	-0.163^{**}	-0.162^{**}	-0.164^{**}
	(0.054)	(0.055)	(0.056)	(0.056)
Longest line normalized	-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Number of lines normalized	-0.315^{***}	–	-0.327^{***}	–
	(0.020)		(0.020)	
Easy treatment dummy	2.068^{***}	2.126^{***}	2.218^{***}	2.287^{***}
	(0.099)	(0.100)	(0.104)	(0.106)
Difficult treatment dummy	-1.662^{***}	-1.700^{***}	-1.729^{***}	-1.767^{***}
	(0.058)	(0.059)	(0.060)	(0.062)
Letter dummies	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes
AIC	8337.8	8180.5	8171.7	8014.6

We provide the coefficient estimates and the standard errors in parentheses. We do not provide the estimates of the intercepts, the Letter dummies, or the subject-specific dummies in the fixed effects regressions. AIC refers to the Akaike information criterion (Akaike, 1974). Each regression has 9200 observations. *** denotes $p < 0.001$, ** denotes $p < 0.01$, * denotes $p < 0.05$, and † denotes $p < 0.1$.

In every specification, we see that the high load coefficient is negative. This implies that choices are worse in the high cognitive load treatment. We also find that the accuracy of the choice decreases when there is a larger number of lines (choice overload effects) and decreases in the difficulty of the decision. Additionally, we see that the accuracy decreases in the length of the longest line. This result could be interpreted as suggesting that subjects are worse at judging longer lines than shorter lines. This explanation is consistent with Weber's law. On the other hand, it is possible that the subjects expended less effort on trials with longer lines because the subjects knew that they would earn more on these trials than on trials with shorter lines. These effort-wealth effects could also explain the negative coefficient estimates for the Longest line variable.

In the appendix, we also report additional analyses that investigate the optimality of choice. We conduct the analogous tobit regressions with the Longest line minus the selected line as dependent variable (Table $A1$). Our results are not changed. Together these results imply that the availability of cognitive resources affects the quality of the choice.

4.3 Quality of searches

The analysis above suggests that the high cognitive load treatment implied worse choices. Here we explore the effect of the cognitive load on the quality of the searches. We define the *View clicks* variable as the number of total line view clicks during the search stage. We conduct an analysis identical to Table 6, with the exception that the dependent variable is View clicks and the regression is linear, not logistic. Table 7 summarizes this analysis.

Table 7 Regressions of the View clicks variable

	(1)	(2)	(3)	(4)
High load	-0.339^{***}	-0.346^{***}	-0.340^{***}	-0.348^{***}
	(0.049)	(0.049)	(0.040)	(0.040)
Longest line normalized	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.002^{***}
	(0.001)	(0.001)	(0.0004)	(0.0004)
Number of lines normalized	1.082^{***}	–	1.083^{***}	–
	(0.017)		(0.014)	
Easy treatment dummy	-1.459^{***}	-1.470^{***}	-1.421^{***}	-1.431^{***}
	(0.060)	(0.060)	(0.050)	(0.050)
Difficult treatment dummy	0.654^{***}	0.639^{***}	0.654^{***}	0.643^{***}
	(0.060)	(0.059)	(0.050)	(0.050)
Letter dummies	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes
AIC	41894.2	41815.7	38318.0	38221.7

We provide the coefficient estimates and the standard errors in parentheses. We do not provide the estimates of the intercepts, the Letter dummies, or the subject-specific dummies in the fixed effects regressions. AIC refers to the Akaike information criterion (Akaike, 1974). Each regression has 9200 observations. *** denotes $p < 0.001$, ** denotes $p < 0.01$, * denotes $p < 0.05$, and † denotes $p < 0.1$.

Here we see fewer View clicks in the high load than in the low load. This suggests that the cognitive load manipulation is affecting the quality of the searches. We also observe that View clicks is increasing in the number of available lines. Further, we observe that View clicks is decreasing in the size of the longest line. This suggests that subjects expended less effort in the searches involving longer lines. Perhaps more surprisingly, we observe more View clicks in the Difficult treatment and fewer in the Easy treatment. Although we note that Reutskaja et al. (2011), Krajbich, Armel, and Rangel (2010), and Krajbich and Rangel (2011) find similar results.

In the appendix, we also report on additional analyses that investigate the optimality of searches. These analyses are similar to Table 7 but with dependent variables that capture the number of unique line views (Table $A2$), the number of times the longest line was viewed (Table $A3$), and the average of the line lengths viewed weighted by their time viewed (Table $A4$). In each of these analyses, we find that the subjects in the high cognitive load treatment perform worse searches than in the low cognitive load treatment.

4.4 Relationship between choice and search

We observe both that choices are worse in the high cognitive load treatment and that searches are worse in the high cognitive load treatment. A natural question is whether the worse searches are causing the worse choices. There is a literature that posits that suboptimal choice occurs because subjects do not consider every object in the choice set, but only a subset. Further this consideration set is not typically observable to the experimenter. However, due to our design, we are able to observe whether subjects viewed the longest line.

Among the 9109 trials where subjects viewed the longest line, there are 6354 observations where the longest line was not selected. However, among the 91 trials where subjects did not view the longest line there are 73 observations where the longest line was not selected. Therefore in our data, 98.9% of the suboptimal choices occurred in trials where the subject viewed the longest line. This suggests that the bulk of our suboptimal choices can be explained due to imperfect perception rather than not considering the longest line.

In Table 6 above, we explored whether subjects optimally selects the longest line by conducting regressions with the Selected longest line variable. Another question to ask is whether subjects selected the longest line, among the lines that were viewed. We define the *Selected longest line viewed* variable as a 1 if the longest line among those viewed was selected, and a 0 otherwise. We conduct an analysis, similar to Table 6 but rather than using the Selected longest line variable, we employ the Selected longest line viewed variable. We summarize these regressions in Table 8.

Table 8 Logistic regressions of Selected longest line viewed variable

	(1)	(2)	(3)	(4)
High load	-0.142^{**}	-0.148^{**}	-0.145^{**}	-0.148^{**}
	(0.054)	(0.055)	(0.056)	(0.056)
Longest line normalized	-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Number of lines normalized	-0.304^{***}	–	-0.314^{***}	–
	(0.020)		(0.020)	
Easy treatment dummy	2.122^{***}	2.186^{***}	2.232^{***}	2.307^{***}
	(0.102)	(0.103)	(0.105)	(0.106)
Difficult treatment dummy	-1.661^{***}	-1.703^{***}	-1.726^{***}	-1.769^{***}
	(0.058)	(0.059)	(0.060)	(0.062)
Letter dummies	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes
AIC	8304.9	8133.5	8176.0	8003.9

We provide the coefficient estimates and the standard errors in parentheses. We do not provide the estimates of the intercepts, the Letter dummies, or the subject-specific dummies in the fixed effects regressions. AIC refers to the Akaike information criterion (Akaike, 1974). Each regression has 9200 observations. *** denotes $p < 0.001$, ** denotes $p < 0.01$, * denotes $p < 0.05$, and † denotes $p < 0.1$.

Even when we restrict attention to the set of viewed lines, we still find evidence that subjects in the high load treatment make worse choices than in the low load treatment. Therefore, consideration set effects cannot fully explain the relationship between cognitive load and the Selected longest variable, as summarized in Table 6. Additionally, we note a negative relationship between the quality of choices among the lines that were viewed and the length of the longest line. We note that while this cannot be explained by consideration set effects, we cannot distinguish between the Weber's law explanation and the effort-wealth effects explanation. Finally, we note the negative relationship between selecting the longest line viewed and the number of lines in the choice set. Reutskaja et al. (2011) find a similar relationship in their data.

We also conduct an analysis, found in the appendix, that conducts the analogous analysis by employing tobit regressions on the variable that is the length of the maximum line viewed minus the length of the line selected (Table $A5$). Our results are not changed. Together our results suggest that the consideration set effects do not fully explain the suboptimal choices.

4.5 Multinomial discrete choice analysis and the nature of the stochastic utility

An assumption in multinomial discrete choice analysis is that choice is stochastic because of an unobserved stochastic component in the utility function.[13] A common specification in these random utility models (RUM) is that there is a non-stochastic component of the utility function and an additive stochastic component. For example, option j would have utility:

$$U_j = V_j + \epsilon_j \ ,$$

where V_j is the non-stochastic component and ϵ_j is the random component. RUMs typically assume that agents select the item with the largest realized utility. Specifically, a choice of i from the set $K = \{1, ..., k\}$ arises when:

$$V_i + \epsilon_i \geq V_j + \epsilon_j \text{ for every } j \in K.$$

Further, the non-stochastic components to the RUMs are not typically observable. Therefore the researcher includes a set of observable features possibly relevant to the choice j, $\overline{x_j} = (x_{j1}, ..., x_{jn})$. In order to account for the effect of each of these factors, the analyst also estimates $\overline{\beta} = (\beta_1, ..., \beta_n)$. In these settings, the non-stochastic component is $V_j = \overline{\beta} * \overline{x_j}$. However, in our setting, the length of the line is the only relevant attribute. Therefore the non-stochastic component of option j simplifies to:

$$V_j = \beta * Length_j,$$

where β is a scalar.

We also note that there can be a range of specifications of the stochastic component. For instance, ϵ_j might be assumed to be normally distributed. On the other hand, the stochastic component might also be assumed to have the Gumbel distribution, $e^{-e^{-\epsilon}}$. (Confusingly, this is also referred to as the Type I extreme-value distribution, the double exponential distribution,

[13] See McFadden (1974, 1976, 1981, 2001).

and the log-Weibull distribution.) In our experiment, we can perfectly observe the objective lengths of the lines and the choices made by the subjects. We can therefore run specifications that employ either of these assumptions of the error distribution and observe which provides a better fit of the data, given the objective lengths of the lines in the choice set.

We run one specification where the stochastic component has the Gumbel distribution and is identically distributed for every option. As McFadden (1974) and Yellot (1977) show, this structure implies the Luce (1959a) stochastic choice model, whereby the probability that option j is selected from set K is:

$$P(j) = \frac{e^{\beta * Length_j}}{\sum_{k \in K} e^{\beta * Length_k}}.$$

We denote this *Conditional Logistic* model as specification (1).

We also run a specification where the stochastic component is assumed to have a normal distribution and is independently and identically distributed for every option. Yellot (1977) shows that this corresponds to Case V of Thurstone (1927a). We refer to this *Multinomial Probit* model as "Multi Probit 1" and denote it as specification (2).

Further, we run a specification where the stochastic component is assumed to be Gumbel but the options are not identically distributed. Specifically, each option has a stochastic component distributed $e^{-e^{-\frac{\epsilon}{\theta_i}}}$ where θ_i varies by the option. This specification is the Heteroschedastic Extreme-Value (HEV) model, introduced by Bhat (1995). For identification purposes, the final two options are assumed to be identically distributed with the unit scale: $\theta_k = \theta_{k-1} = 1$. We denote the HEV model as specification (3).

Finally, we run a specification where the stochastic component is assumed to be normally but non-identically distributed. This Multinomial Probit specification assumes that the standard deviations of the options can be different but that they are also independently distributed. Note that similar to the HEV model, for identification purposes, we assume that the standard deviation of the final two choices are identical. We refer to this Multinomial Probit model as "Multi Probit 2" and denote it as specification (4).

Note that we exclude observations where subjects did not specify a choice before time expired. Therefore, the numbers of trials as reported in Table 3 are different than those reported below in this subsection.

We report the Akaike Information Criterion (AIC, Akaike, 1974) and the Bayesian Information Criterion (BIC, Schwarz, 1978) for each model, restricted to a particular number of lines treatment. We also report the estimate of β for each model in each setting. These analyses[14] are summarized in Table 9. Note that for the case of 2 Lines, the Conditional Logistic regression is identical to the HEV specification, and the Multinomial Probit 1 is identical to the Multinomial Probit 2 specification. Therefore, we do not report specifications (3) and (4) for the 2 Lines treatment.

Table 9: Comparisons of different multinomial discrete choice models

		Cond Logit (1)	Multi Probit 1 (2)	HEV (3)	Multi Probit 2 (4)	Trials
2 Lines	β est.	0.131	0.098	–	–	1785
	AIC	1417	1432			
	BIC	1422	1437			
3 Lines	β est.	0.128	0.086	0.118	0.067	1871
	AIC	2088	2140	2078	2145	
	BIC	2094	2146	2089	2156	
4 Lines	β est.	0.115	0.076	0.121	0.084	1826
	AIC	2718	2801	2709	2820	
	BIC	2723	2807	2726	2837	
5 Lines	β est.	0.110	0.108	0.113	0.116	1780
	AIC	3181	3383	3186	3282	
	BIC	3186	3389	3208	3304	
6 Lines	β est.	0.094	0.062	0.070	0.046	1780
	AIC	3775	3808	3613	3684	
	BIC	3780	3813	3641	3711	

We provide the estimates of β, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) for the various models restricted to treatments with identical numbers of lines. Each of the estimates for β are significantly different from 0 with $p < 0.001$.

For both AIC and BIC, every value for the Conditional Logit model (1) is lower than that for the analogous Multinomial Probit 1 model (2). Additionally for both measures, every

[14] Each specification was executed with the MDC (multinomial discrete choice) procedure in SAS. Specification (1) was performed with the *clogit* option. Specification (2) was performed with the *mprobit* option. Specification (3) was performed with the *hev* option and the Hardy integration method. Specification (4) was performed with the *mprobit* option.

value for the HEV model (3) is lower than that for the analogous Multinomial Probit 2 model (4). We interpret these results as suggesting that the models that assume that errors have a Gumbel distribution provide a better fit than comparable models that assume that errors have a normal distribution. However, we note that the estimates of β vary among the models, and this is perhaps affecting our results. In order to address this possibility, we offer an analysis, identical to that summarized in Table 9, however we add an additional restriction that $\beta = 0.1$. This analysis is summarized in Table 10.

Table 10: Comparisons of different restricted multinomial discrete choice models

		Cond Logit (1)	Multi Probit 1 (2)	HEV (3)	Multi Probit 2 (4)	Trials
2 Lines	AIC	1435	1430	–	–	1785
	BIC	1435	1430			
3 Lines	AIC	2116	2154	2087	2154	1871
	BIC	2116	2154	2093	2160	
4 Lines	AIC	2729	2903	2722	2810	1826
	BIC	2729	2903	2733	2821	
5 Lines	AIC	3186	3317	3190	3241	1780
	BIC	3186	3317	3207	3257	
6 Lines	AIC	3776	4153	3691	4097	1780
	BIC	3776	4153	3713	4119	

We provide the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) for the various models restricted to treatments with identical numbers of lines. We have restricted $\beta = 0.1$ in each specification.

Similar to the analysis summarized in Table 9, with the exception of the 2 Lines treatment, both the AIC and BIC are lower for the specifications with Gumbel errors than for normal errors. In 17 of 18 comparisons, the AIC of the Gumbel error specification is lower than that for the normal error specification. Likewise, in 17 of 18 comparisons, the BIC of the Gumbel error specification is lower than that for the normal error specification. We interpret these results as evidence that the assumption that the errors have a Gumbel distribution is a better fit than the assumption that the errors have a normal distribution.

4.6 Memory decay and choice

Reutskaja, Nagel, Camerer, and Rangel (2011) report that the quality of choices tend to be diminishing in number of items viewed between the last item viewed and the best item viewed. Here we examine whether our subjects exhibit similar behavior consistent with memory decay.

Recall Table 5, which demonstrates the relationship between the quality of choice and the letter label of the longest line. There appears to be a relationship between the quality of the choice and number of letters alphabetically between the letter label of the longest line and the last letter label in the choice set. Below, we test whether there is such a relationship.

We introduce the variable *Distance from last*, which provides a measure of the alphabetic distance between the letter label of the longest line and the last letter label in the choice set. For instance, in the 2 Line treatment, if line A is the longest then the variable is 1 and if line B is the longest then it is 0. In the 3 Line treatment, if A is the longest then the variable is 2, if B is the longest then it is 1, and if C is the longest then 0. We include Distance from the last as an independent variable. We also include specifications with the interaction between the High load dummy and the Distance from last variable. For identification reasons, we do not include the Letter dummy variables. We summarize these regressions in Table 11.

Table 11 Logistic regressions of the Selected longest line variable

	(1)	(2)	(3)	(4)
High load	-0.163^{**}	$-0.138^{\dagger}$	-0.168^{***}	-0.138
	(0.055)	(0.082)	(0.056)	(0.085)
Distance from last	-0.245^{***}	-0.237^{***}	-0.259^{***}	-0.250^{***}
	(0.023)	(0.030)	(0.023)	(0.030)
High load * Distance from last	–	-0.016	–	-0.019
		(0.039)		(0.040)
Longest line normalized	-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Number of lines normalized	-0.194^{***}	-0.194^{***}	-0.199^{***}	-0.199^{***}
	(0.023)	(0.023)	(0.023)	(0.023)
Easy treatment dummy	2.113^{***}	2.113^{***}	2.270^{***}	2.271^{***}
	(0.100)	(0.100)	(0.105)	(0.105)
Difficult treatment dummy	-1.676^{***}	-1.677^{***}	-1.746^{***}	-1.746^{***}
	(0.059)	(0.059)	(0.061)	(0.061)
Letter dummies	*No*	*No*	*No*	*No*
Fixed effects	*No*	*No*	*Yes*	*Yes*
AIC	8220.1	8221.9	8049.6	8049.2

We provide the coefficient estimates and the standard errors in parentheses. We do not provide the estimates of the intercepts or the subject-specific dummies in the fixed effects regressions. AIC refers to the Akaike information criterion (Akaike, 1974). Each regression has 9200 observations. *** denotes $p < 0.001$, ** denotes $p < 0.01$, * denotes $p < 0.05$, and † denotes $p < 0.1$.

In every specification, we observe a negative relationship between Distance from last and the quality of the choice. This is consistent with the hypothesis suggested by Table 5. We also note that there is not a significant interaction between the cognitive load and the Distance from last variable. Additionally, each of the other coefficients estimates are relatively unchanged from the analysis summarized in Table 6. The exception to this is that the estimate of the High load dummy coefficient is not robust to the specifications that include the interaction between cognitive load and Distance from last.

One explanation for the negative coefficient estimates for the Distance from last variable is that subjects view the lines in alphabetical order (A then B then C etc.). However, lines viewed in the more distant past are recalled with a lower precision: either the location of the longest line or the length of the longest line. To explore this possibility, we define the variable *Time since longest* to be the time elapsed since subjects viewed the longest line when the trial ended. Table 12 demonstrates the relationship between the Time since longest variable and the letter label of the longest line.

Table 12: Time since longest line by number of lines and letter label of the longest

	A	B	C	D	E	F
2 Lines	2.491 s	1.452 s	–	–	–	–
3 Lines	2.801 s	3.464 s	1.347 s	–	–	–
4 Lines	3.150 s	3.335 s	3.232 s	1.810 s	–	–
5 Lines	3.404 s	3.472 s	3.664 s	3.125 s	2.461 s	–
6 Lines	4.117 s	3.986 s	3.627 s	3.270 s	3.211 s	1.800 s

Table 12 suggests that there is a negative relationship between the Time since longest variable and the number of letter labels alphabetically between that for the longest line and the last letter label in the choice set. Here we test whether there is such a relationship. To do so, we conduct an analysis similar to Table 11, however we employ the Time since longest variable rather than the Distance from last variable. We summarize these regressions in Table

13. We interpret these results with caution due to the possibility of endogeneity introduced by including the Time since longest variable.

Table 13 Logistic regressions of the Selected longest line variable

	(1)	(2)	(3)	(4)
High load	-0.099	$-0.147^{\dagger}$	-0.092	-0.124
	(0.061)	(0.080)	(0.063)	(0.084)
Time since longest	-0.288^{***}	-0.296^{***}	-0.318^{***}	-0.323^{***}
	(0.008)	(0.012)	(0.009)	(0.013)
High load * Time since longest	–	0.014	–	0.010
		(0.015)		(0.016)
Longest line normalized	-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Number of lines normalized	-0.276^{***}	-0.275^{***}	-0.291^{***}	-0.291^{***}
	(0.022)	(0.022)	(0.023)	(0.023)
Easy treatment dummy	2.534^{***}	2.531^{***}	2.650^{***}	2.648^{***}
	(0.113)	(0.113)	(0.119)	(0.119)
Difficult treatment dummy	-1.613^{***}	-1.613^{***}	-1.684^{***}	-1.684^{***}
	(0.066)	(0.066)	(0.069)	(0.069)
Letter dummies	*No*	*No*	*No*	*No*
Fixed effects	*No*	*No*	*Yes*	*Yes*
AIC	6802.6	6803.7	6590.8	6592.5

We provide the coefficient estimates and the standard errors in parentheses. We do not provide the estimates of the intercepts or the subject-specific dummies in the fixed effects regressions. AIC refers to the Akaike information criterion (Akaike, 1974). Each regression has 9200 observations. *** denotes $p < 0.001$, ** denotes $p < 0.01$, * denotes $p < 0.05$, and † denotes $p < 0.1$.

In every specification, there is a negative relationship between the time elapsed since the longest line was viewed at the end of the trial and the quality of the choice. On the other hand, we do not find evidence that this relationship is affected by the cognitive load. Further, we observe qualitatively similar results to those found above, with the exception of the estimate for the High load variable. In none of the specifications is the estimate significant at 0.05.

It seems that choices are worse when the longest line is more alphabetically distant from the last letter label in the choice set and the longer the time since the longest line was viewed. Taken together, our results are consistent with memory decay: lines viewed in the more distant past are remembered with lower precision. We note that these results are consistent with limited cognition but we also note that we do not find a relationship between the memory decay effects and the cognitive load manipulation. Finally, we note that these effects might be exacerbated by the relatively smaller spatial distance between F region and the F box compared with the larger spatial distance between the A region and the A box.

4.7 Attention and choice

Testing for evidence consistent with memory decay is not the only such investigation on the effects of limited cognitive resources. Here we investigate the role of attention in choice.

Research finds that the time that a subject spends viewing (or fixated on) an object in a choice setting is associated with a higher likelihood of selecting the object.[15] Additionally, the visual psychology literature also finds that spatial resolution of abstract objects and visual information processing are enhanced by attention.[16]

One measure of attention is the total time spent viewing a line. In Table 14, we summarize the *Time viewing* variable by the number of lines treatment and the letter label.

Table 14: Time viewing by number of lines and letter label

	A	B	C	D	E	F
2 Lines	6.338 s	6.909 s	–	–	–	–
3 Lines	4.356 s	3.675 s	5.195 s	–	–	–
4 Lines	3.238 s	2.966 s	2.953 s	4.104 s	–	–
5 Lines	2.733 s	2.443 s	2.367 s	2.454 s	3.262 s	–
6 Lines	2.263 s	2.080 s	1.993 s	2.005 s	1.975 s	2.938 s

In Table 15, we report the Time viewing variable but restricted to the letter label of the longest line.

Table 15: Total time viewing longest by number of lines and letter label of the longest

	A	B	C	D	E	F
2 Lines	8.410 s	9.028 s	–	–	–	–
3 Lines	7.020 s	6.010 s	7.805 s	–	–	–
4 Lines	5.622 s	5.252 s	5.074 s	6.351 s	–	–
5 Lines	5.047 s	4.374 s	4.351 s	4.170 s	5.040 s	–
6 Lines	3.992 s	3.772 s	3.600 s	3.778 s	3.806 s	4.994 s

[15] See Armel, Beaumel, and Rangel (2008), Armel and Rangel (2008), Krajbich, Armel, and Rangel (2010), and Krajbich and Rangel (2011).

[16] For instance, see Yeshurun and Carrasco (1998), Carrasco and McElree (2001), Carrasco, Williams, and Yeshurun (2002), and Liu, Abrams, and Carrasco (2009).

Comparing Tables 5 and 15, there appears to be a relationship between the time spent viewing the longest line and the likelihood that the longest line was selected. Here we test this conjecture. We perform an analysis similar to Tables 11 and 13 but with Time viewing longest as an independent variable. We summarize these regressions in Table 16. Similar to the analysis summarized in Table 13, we interpret these results with caution due to the possibility of endogeneity introduced by including the Time viewing longest variable.

Table 16 Logistic regressions of the Selected longest line variable

	(1)	(2)	(3)	(4)
High load	-0.105	0.030	$-0.112^{\dagger}$	0.019
	(0.065)	(0.120)	(0.067)	(0.125)
Time viewing longest	0.536^{***}	0.556^{***}	0.561^{***}	0.579^{***}
	(0.014)	(0.020)	(0.015)	(0.021)
High load * Time viewing longest	–	-0.035	–	-0.034
		(0.026)		(0.027)
Longest line normalized	-0.003^{***}	-0.003^{***}	-0.003^{***}	-0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Number of lines normalized	0.121^{***}	0.122^{***}	0.135^{***}	0.137^{***}
	(0.025)	(0.025)	(0.026)	(0.026)
Easy treatment dummy	2.297^{***}	2.293^{***}	2.396^{***}	2.391^{***}
	(0.112)	(0.112)	(0.120)	(0.120)
Difficult treatment dummy	-1.387^{***}	-1.387^{***}	-1.441^{***}	-1.441^{***}
	(0.070)	(0.070)	(0.073)	(0.073)
Letter dummies	No	No	No	No
Fixed effects	No	No	Yes	Yes
AIC	6054.4	6054.6	5974.5	5975.0

We provide the coefficient estimates and the standard errors in parentheses. We do not provide the estimates of the intercepts or the subject-specific dummies in the fixed effects regressions. AIC refers to the Akaike information criterion (Akaike, 1974). Each regression has 9200 observations. *** denotes $p < 0.001$, ** denotes $p < 0.01$, * denotes $p < 0.05$, and † denotes $p < 0.1$.

In every specification, the quality of the choice is increasing in the time viewing the longest line.[17] A similar result is reported by Krajbich and Rangel (2011). Also in every specification, we do not find a significant interaction between the cognitive load and the time viewing the longest. We also find a similar relationship involving the difficulty treatments and the length

[17] We find similar results if we measure attention with the number of view clicks on the longest line or whether subjects viewed the longest line 2 or more times.

of the longest line variable. However, we observe that the Number of lines coefficient estimate is positive. This is likely related to the apparently negative relationship between Time viewing longest variable and the longest line variable.

Our results suggest that (endogenous) attention is related to choice. However, we do not find that the cognitive load manipulation affects this relationship.

5 Conclusion

We observe subjects in an "idealized" choice setting where we know the true preferences of the subjects, but subjects have an imperfect perception of their preferences. The objects of choice are lines that vary in length and subjects are paid an amount increasing in the length of the selected line. This feature allows us to make unambiguous conclusions about the optimality of choices. Subjects also make their choices in different cognitive load treatments, which are designed to manipulate their available cognitive resources.

Are there brains in choice? Our results suggest a qualified "yes." In our choice setting, we found that differences in available cognitive resources, as manipulated by cognitive load, implied differences in both choice and search. Further, we observe that cognitive load affects the quality of the choice, even when we restrict attention to the set of observed lines. This suggests that the relatively low quality searches in the high cognitive load treatment are not the primary cause of the suboptimal choices.

Additionally, we find evidence of choice overload in our setting, where the choice set is small and the objects are simple. We also observe limited cognition effects, consistent with memory decay and attention. However, we note that these effects that are consistent with memory decay and attention are not affected by the cognitive load manipulation.

Many random utility models posit that there is a non-stochastic component and an additive stochastic component, which is also referred to as an error term. An additional advantage of our design, where we know the true preferences of the subjects, is that we are well-positioned to test the nature of these errors. We run specifications that assume normally distributed errors and analogous specifications that assume errors have a Gumbel distribution. We find that in 17 of 18 pairwise comparisons, the Gumbel specifications provide a better fit. We interpret this as suggesting that the assumption of Gumbel errors is more accurate than the assumption of normal errors.

We admit that there is much work to be done on the topic. We are interested to learn the insights gleaned from eye-tracking and neuroeconomics techniques in our setting.[18] We are also interested in whether our results on Gumbel errors extend to other stimuli with uncountable measures, for example brightness, loudness, etc. Whereas our design entailed objects valued on only a single attribute, we hope that future designs will study behavior in settings where the objects are valued based on multiple attributes (Gabaix et al., 2006; Sanjurjo, 2015, 2017). Specifically, we are interested to learn if classic multiple attribute effects, such as the decoy effect, can be replicated in this setting and if the attributes interact as compliments or substitutes.[19]

Further, alternate payment schemes could yield additional insights. For instance, rather than paying an amount that increases in the length of the selected line, consider a fixed payment if the longest line in the choice set is selected. This could help us distinguish between the Weber's law explanation and the effort-wealth effects explanation for the negative relationship between the quality of choice and the length of the lines.

Finally, in our design, subjects were forced to select only a single object from the choice set. We are interested to study behavior if subjects are not constrained to select only one, and are able to select more than one object. Such a multiple selection could be interpreted as indifference if the received object was randomly selected among the chosen objects. We leave these and other interesting questions to future research.

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[18] For instance, see Summerfield and Tsetsos (2012).

[19] See Tsetsos, Chater, and Usher (2012) for a different design in a multi-attribute experiment.

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6 Appendix

6.1 More on the quality of choices

In order to investigate the optimality of choices, in Table 6 we summarized logistic regressions of the Selected longest variable. Here we perform the analogous exercise but we analyze the *Longest minus selected variable*, defined to be the length of the longest line minus the length of the selected line. As this variable is bounded below by 0 we perform tobit regressions. The regressions are otherwise identical to those in Table 6. We summarize these tobit regressions in Table $A1$.

Table $A1$ Tobit regressions of Longest minus selected variable

	(1)	(2)	(3)	(4)
High load	6.745***	6.987***	6.641***	6.872***
	(1.832)	(1.835)	(1.784)	(1.786)
Longest line normalized	0.133***	0.132***	0.131***	0.131***
	(0.020)	(0.020)	(0.019)	(0.019)
Number of lines normalized	10.007***	–	9.915***	–
	(0.664)		(0.649)	
Easy treatment dummy	−53.686***	−53.828***	−56.245***	−56.505***
	(2.967)	(2.975)	(2.987)	(2.996)
Difficult treatment dummy	34.991***	34.850***	34.379***	34.180***
	(2.092)	(2.096)	(2.044)	(2.047)
Letter dummies	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes
AIC	35721	35674	35445	35398

We provide the coefficient estimates and the standard errors in parentheses. We do not provide the estimates of the intercepts, the Letter dummies, or the subject-specific dummies in the fixed effects regressions. AIC refers to the Akaike information criterion (Akaike, 1974). Each regression has 9200 observations. *** denotes $p < 0.001$, ** denotes $p < 0.01$, * denotes $p < 0.05$, and † denotes $p < 0.1$.

Similar to Table 6, the accuracy of the choice decreases when there is a larger number of lines, decreases in the length of the longest line, and decreases in the difficulty of the decision. Further, in every specification, we see that the high load coefficient is positive. This implies that choices are worse in the high cognitive load treatment.

6.2 More on the quality of searches

In order to investigate the optimality of searches, we summarized the regressions of the View clicks variable (Table 7). Here we perform the analogous exercise but we analyze the *Unique lines viewed* variable, defined to be the number of unique lines viewed during a trial. This analysis is summarized in Table $A2$.

Table $A2$ Regressions of Unique lines viewed variable

	(1)	(2)	(3)	(4)
High load	-0.027^{***}	-0.027^{***}	-0.027^{***}	-0.027^{***}
	(0.008)	(0.008)	(0.007)	(0.007)
Longest line normalized	-0.0002^{*}	-0.0002^{*}	-0.0002^{*}	-0.0002^{*}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Number of lines normalized	0.981^{***}	–	0.982^{***}	–
	(0.003)		(0.002)	
Easy treatment dummy	0.008	0.008	$0.014^{\dagger}$	0.014
	(0.010)	(0.010)	(0.009)	(0.009)
Difficult treatment dummy	-0.010	-0.010	-0.003	-0.003
	(0.010)	(0.010)	(0.009)	(0.009)
Letter dummies	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes
AIC	8231.0	8322.5	6483.0	6583.5

We provide the coefficient estimates and the standard errors in parentheses. We do not provide the estimates of the intercepts, the Letter dummies, or the subject-specific dummies in the fixed effects regressions. AIC refers to the Akaike information criterion (Akaike, 1974). Each regression has 9200 observations. *** denotes $p < 0.001$, ** denotes $p < 0.01$, * denotes $p < 0.05$, and † denotes $p < 0.1$.

Similar to Table 7, we find evidence of worse searches in the high cognitive load treatment. Also interestingly, we find that the Number of lines coefficient is close to, but smaller than, 1. This suggests that adding another line to the choice set implies that the number of unique lines viewed increases by less than 1. Next we investigate the optimality of searches by performing the analogous analysis but with the *View clicks on longest* variable, defined to be the number of times that the longest line was viewed during a trial. This analysis is summarized in Table $A3$.

Table $A3$ Regressions of View clicks on longest variable

	(1)	(2)	(3)	(4)
High load	-0.128^{***}	-0.136^{***}	-0.128^{***}	-0.137^{***}
	(0.020)	(0.020)	(0.018)	(0.017)
Longest line normalized	-0.0003	$-0.0004^{\dagger}$	-0.0003	-0.0004^{*}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Number of lines normalized	-0.124^{***}	–	-0.123^{***}	–
	(0.007)		(0.006)	
Easy treatment dummy	-0.406^{***}	-0.413^{***}	-0.390^{***}	-0.397^{***}
	(0.025)	(0.024)	(0.022)	(0.021)
Difficult treatment dummy	-0.099^{***}	-0.110^{***}	-0.099^{***}	-0.109^{***}
	(0.025)	(0.024)	(0.022)	(0.021)
Letter dummies	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes
AIC	25678.8	25304.9	23533.6	23028.9

We provide the coefficient estimates and the standard errors in parentheses. We do not provide the estimates of the intercepts, the Letter dummies, or the subject-specific dummies in the fixed effects regressions. AIC refers to the Akaike information criterion (Akaike, 1974). Each regression has 9200 observations. *** denotes $p < 0.001$, ** denotes $p < 0.01$, * denotes $p < 0.05$, and † denotes $p < 0.1$.

We find evidence that subjects in the high cognitive load treatment view the longest line a smaller number of times than the subjects in the low cognitive load treatment. Again, similar to Table 7 and $A2$, we see evidence that the high cognitive load negatively affects search.

Interestingly, the estimates for both the Easy treatment dummy and the Difficult treatment dummy variables are negative. Perhaps this is the case because in the Easy treatment, there is not a need to verify the longest line with an additional click. And perhaps in the Difficult treatment, finding the longest line is excessively difficult.

We conduct another analysis of the quality of the searches, similar to the analysis above. However, as the dependent variable we employ *Line lengths weighted by time* variable, defined to be the average of the line lengths viewed weighted by the fraction of the trial in which it was viewed. This is summarized in Table $A4$.

Table $A4$ Regressions of Line lengths weighted by time variable

	(1)	(2)	(3)	(4)
High load	-3.536^{***}	-3.478^{***}	-3.531^{***}	-3.465^{***}
	(0.460)	(0.459)	(0.404)	(0.404)
Longest line normalized	0.869^{***}	0.870^{***}	0.869^{***}	0.870^{***}
	(0.005)	(0.005)	(0.004)	(0.004)
Number of lines normalized	-3.148^{***}	–	-3.180^{***}	–
	(0.163)		(0.144)	
Easy treatment dummy	-13.172^{***}	-13.190^{***}	-12.850^{***}	-12.840^{***}
	(0.564)	(0.564)	(0.498)	(0.498)
Difficult treatment dummy	5.496^{***}	5.495^{***}	5.892^{***}	5.907^{***}
	(0.563)	(0.562)	(0.498)	(0.497)
Letter dummies	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes
AIC	83013.3	82913.1	80271.3	80166.6

We provide the coefficient estimates and the standard errors in parentheses. We do not provide the estimates of the intercepts, the Letter dummies, or the subject-specific dummies in the fixed effects regressions. AIC refers to the Akaike information criterion (Akaike, 1974). Each regression has 9200 observations. *** denotes $p < 0.001$, ** denotes $p < 0.01$, * denotes $p < 0.05$, and † denotes $p < 0.1$.

The line lengths weighted by time viewed is significantly smaller in the low cognitive load treatment. Again, we find evidence that subjects in the high cognitive load treatment conduct worse searches.

6.3 More on the relationship between choice and search

In order to investigate the relationship between choice and search, in Table 8 we summarized logistic regressions of the Selected longest line viewed variable. Here we perform the analogous exercise but we analyze the *Longest viewed minus selected variable*, defined to be the length of the longest line viewed minus the length of the selected line. As this variable is bounded below by 0 we perform tobit regressions. The analysis is otherwise identical to those in Table 8. We summarize these tobit regressions in Table $A5$.

Table $A5$ Tobit regressions of Longest viewed minus selected variable

	(1)	(2)	(3)	(4)
High load	5.539**	5.765**	5.473**	5.694**
	(1.791)	(1.793)	(1.759)	(1.761)
Longest line normalized	0.126***	0.125***	0.123***	0.122***
	(0.019)	(0.019)	(0.019)	(0.019)
Number of lines normalized	9.820***	–	9.815***	–
	(0.649)		(0.641)	
Easy treatment dummy	−56.041***	−56.386***	−57.441***	−57.892***
	(2.996)	(3.010)	(3.011)	(3.026)
Difficult treatment dummy	34.258***	34.087***	34.196***	33.976***
	(2.034)	(2.037)	(2.010)	(2.013)
Letter dummies	No	Yes	No	Yes
Fixed effects	No	No	Yes	Yes
AIC	34825	34768	34697	34638

We provide the coefficient estimates and the standard errors in parentheses. We do not provide the estimates of the intercepts, the Letter dummies, or the subject-specific dummies in the fixed effects regressions. AIC refers to the Akaike information criterion (Akaike, 1974). Each regression has 9200 observations. *** denotes $p < 0.001$, ** denotes $p < 0.01$, * denotes $p < 0.05$, and † denotes $p < 0.1$.

Similar to Table 8, the accuracy of the choice decreases when there is a larger number of lines, decreases when the longest line is longer, and decreases in the difficulty of the decision. Further, in every specification, we see that the high load coefficient is positive. This implies that choices are worse in the high cognitive load treatment.