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

Sean Duffy† Steven Gussman‡ John Smith§

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Abstract

We design a choice experiment where the objects are valued according to only a single attribute and we can observe the true preferences of the subject. Subjects are given a choice set involving several lines of various lengths and are told to select one of them. Subjects are instructed 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: the longest line is less likely to be selected and the difference between the length of the selected line and length of the longest 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. 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 have a Gumbel, and not a normal, distribution.

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

JEL: C72, C91

***********PRELIMINARY AND INCOMPLETE************
***********DO NOT CIRCULATE************

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†Rutgers University-Camden, Department of Psychology

‡Rutgers University-Camden, Digital Studies Center

§Corresponding Author; Rutgers University-Camden, Department of Economics, 311 North 5th Street, Camden, New Jersey, USA 08102; Email: smithj@camden.rutgers.edu; Phone: +1-856-225-6319; Fax: +1-856-225-6602

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 additionally 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 infer that a suboptimal action was taken if an intransitive choice was made. In contrast to these two cases, we design an experiment where we have a perfect measure of the preferences of subjects and we can therefore able to determine-without noise-whether subjects selected a suboptimal action.

Next 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 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 the decision sets from previous decisions might interact with subsequent decisions in an idiosyncratic manner that is not discernible to the observer.

We design a choice experiment where the objects 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 physical quantities (Fechner, 1860; Thurstone, 1927a,b). In other words, even where objects have objectively measurable properties, perception of them is imperfect.

Further, this imperfect perception of objective quantities have 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 either 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 cardinal physical quantity.

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 assessment of the objects. This design also allows us to observe the search history of subjects.

Subjects make their choice while under a cognitive load. 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 selected line and length of the longest 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. Our results suggest that, even in our idealized setting, choice is affected by the availability of cognitive resources. We also find choice overload in a setting without complicated objects (our objects

[1] More recent papers that cite these authors include Luce (1994, 2005), Butler (2000), Rieskamp (2008), Fudenberg, Iijima, and Strzalecki (2015), Agranov and Ortoleva (2017), Navarro-Martinez, Loomes, Isoni, Butler, and Alaoui (2017).

are simply line lengths) or without many objects (our largest choice set is 6). 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 have a Gumbel, and not a normal, distribution.

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), 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 understand choice.[2,3] The conceptualization that utility is random has also lead to significant advances in econometrics (McFadden, 1974, 1976, 1981, 2001). Recent attempts to model random choice have included models where the decision maker does not consider the entire set of objects and this is not necessarily observable to the experimenter.[4] It is our position that, while there are likely consideration set effects, the imperfect perception about one's preferences is a key component to 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.[5] Specifically, the agents can reduce the Shannon entropy of the setting by incurring costs associated with attention. The authors show that this implies a random choice specifi-

[2]A partial list of these efforts would include Tversky (1969), Yellott (1977), Falmagne (1978), 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), Gul, Natenzon, and Pesendorfer (2014), Loomes and Pogrebna (2014), Caplin and Dean (2015), Caplin and Martin (2015), Cubitt, Navarro-Martinez, and Starmer (2015), Fudenberg, Iijima, and Strzalecki (2015), Lu (2016), Apesteguia, Ballester, and Lu (2017), Agranov and Ortoleva (2017), Dean and Neligh (2017), Navarro-Martinez, Loomes, Isoni, Butler, and Alaoui (2017), Natenzon (2018), Apesteguia and Ballester (2018), Caplin, Dean, and Leahy (2018), Echenique, Saito, and Tserenjigmid (2018), Koida (2018), and Kovach and Tserenjigmid (2018).

[3]For a partial list from the recent 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).

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

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

cation similar to Luce (1959a). In our experiment there is a similar process as subjects devote cognitive effort in order to better judge the line lengths.

In a closely related paper Reutskaja, Nagel, Camerer, and Rangel (2011) report on a choice experiment that employs eye tracking equipment. The subjects select items under strong 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 experimenter to judge the quality of the choices. The authors find that the quality of choices and the quality of searches decrease in the size of the choice set. Our experiment has a different design in that our subjects have 15 seconds to select among $2-6$ objects. Most notably though, we can objectively determine the quality of the choice since we know the exact lengths of the lines.

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[6] including in strategic settings.[7] 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 cognitive load tends to cause subjects 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 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) look for intransitive choices among pair-wise decisions, while their subjects are under a cognitive load. 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

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

[7] 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 (2018)

to the experimenters. Further, the repeated nature of the experiment makes it difficult to determine if the attributes from previous choices affects subsequent choices (either because the attributes are regarded as complements or substitutes). By contrast our subjects make judgments on objects that have a single 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.

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 search problem where the values are represented by a number. Since subjects cannot fully process the information, despite that there is an objectively optimal solution, the optimal solution is not a common occurrence. Also similar to our setting, subjects must click on the information in order to make it appear. In this way, we can observed the process of deliberation.[8]

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 set of lines that ranged in number between 2 and 6. Each of these numbers of possible lines occurred with probability 0.2 and were drawn with replacement. Subjects were able to only view one line at a time. The lines were labeled by

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

letters in the obvious manner. 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 that corresponds to that particular line. These labels appeared in alphabetical order at the bottom of the screen. A click on a particular label would reveal the corresponding line. To view another line, subjects would click on a its corresponding label. This makes the new line visible and the old line disappear.

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 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 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 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.[9]

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

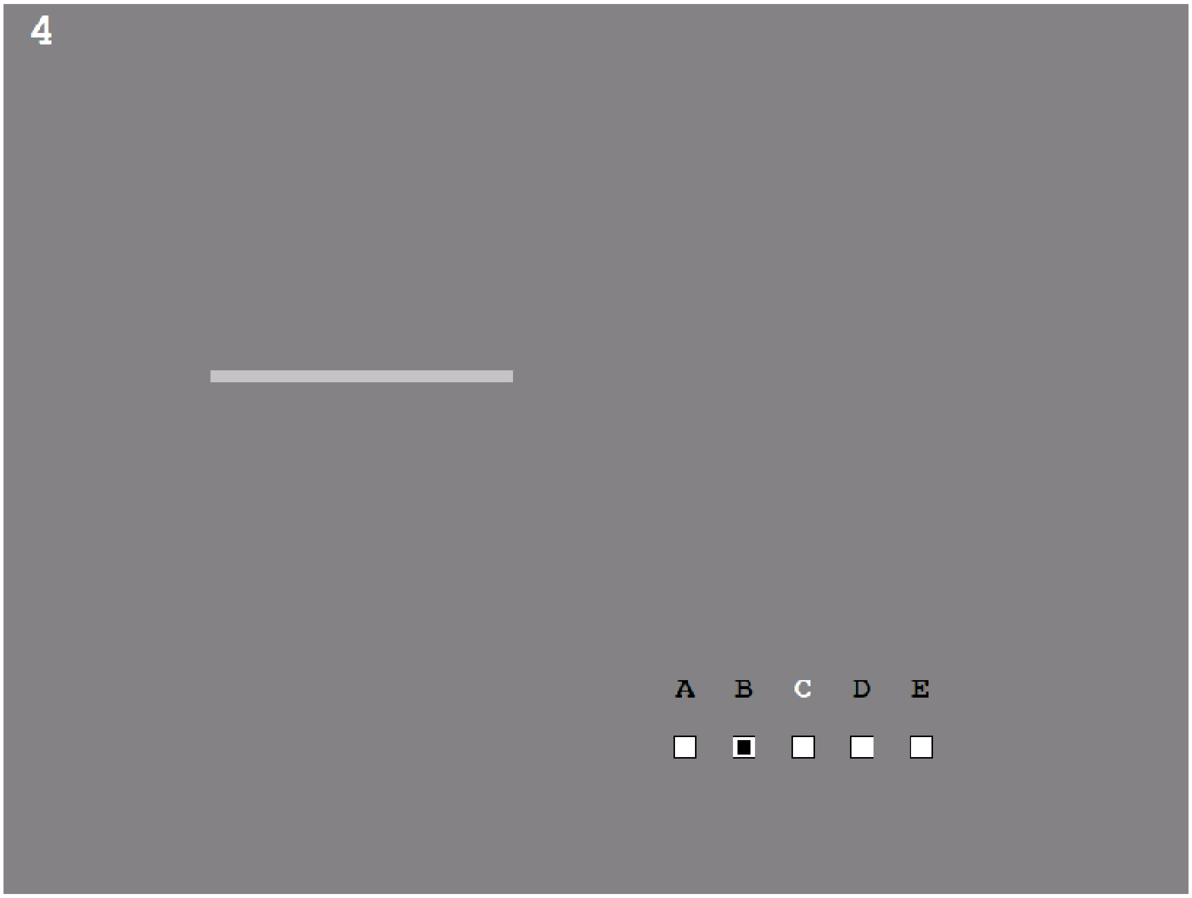

Figure 1: Screenshot where line C is being viewed, line B is currently selected as the longest, and there are 4 seconds remaining.

Subjects were paid for the line that was selected when the 15 second 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 advance to the following screen only when the 15 seconds had expired. Subjects were paid for the length of their selected line at a rate of \$1 per 240 pixels (or \$0.4167 per 100 pixels).

Each line appeared within an invisible box of dimensions 400 pixels by 150 pixels. The lines were randomly offset in the vertical and horizontal direction within these boxes such that there was a minimum of a 20 pixel cushion between the line and the edge of the box.

3.3 Cognitive load treatments

There were 50 trials where the subject was given a 6-digit number to remember, which we refer to as *high load*. There are 50 trials where the subject was given a 1-digit number to remember, which we refer to as *low load*. These were given in random order. Regardless of the load, the subjects were given 5 seconds to commit the number to memory.[10] Subjects would proceed to the following screen only 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, the subjects had unincentivized practice remembering both a 1-digit and a 6-digit number. In contrast to the incentivized portion of the experiment, here the subjects were told if their response was correct. If the response did not contain the correct number of digits then the subjects were directed to repeat the practice memorization task.

Additionally, the subjects had an unincentivized practice on the line selection task. 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

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

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.

3.6 Discussion of the design here?

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 ??? 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 treatment was successful in that the longest line is more likely to be selected in the East treatment. Table 3 characterizes the variable in the 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 with 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. This is evidence of Weber's law. In Table 5 we characterize the variable according to the number of lines and the letter that contained the longest line.

Table 5: Selected longest variable by number of lines and letter containing 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 that contained the longest line. Tables 2 – 5 suggest that the relevant variables need to 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 is 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 that contained 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 on the quality of the choice. We postpone our discussion of this issue until subsection 4.6. 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 $p < 0.1$.

We find that the accuracy of the choice decreases when there is a larger number of lines (choice overload effects), decreases when the longest line is longer (Weber's law), and decreases in the difficulty of the decision (standard random choice effects). Further, 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 see similar results when we conduct the analogous tobit regressions with the Longest line minus the selected line as dependent variable. See Table A??? in the appendix. 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, we now explore the effect of the cognitive load on the searches. To investigate this, 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 that view clicks is lower 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 decreasing in the size of the longest line and is increasing in the number of available lines. Perhaps more surprisingly, we observe more View clicks in the Difficult treatment and fewer in the Easy treatment. That view clicks are increasing in the difficulty of the decision seems to contradict satisficing.

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

4.4 Relationship between choice and search

We observe 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? Manzini and Mariotti (2014) posit that suboptimal choice occurs because the subject does not consider every object in the choice set, but only a subset. Further this consideration set is not typically observable to the experimenter. However, we are able to observe whether the subject viewed the longest line.

Among the 9109 trials where the subject viewed the longest line, there are 6354 observations where the longest line was not selected. However, among the 91 trials where the subject did not view the longest line there are 73 observations where the longest line was not selected. Therefore in our data, 98.86% 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 the subject optimally selects the longest line by conducing regressions with the Selected longest line variable. Another question to ask is whether the subject selected the longest line among those 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 subjects in the low load treatment. 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. This is in Table A???? in the Appendix.

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.[11] 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

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

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

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, $V_j = \overline{\beta} * \overline{x_j}$. 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 different 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, and the 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.

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.

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

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

We also run a specification where the stochastic component is assumed to be normally distributed 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). We note that in our analysis, 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. We report the AIC and the SIC 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 are summarized in Table 9.

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			
	SIC	1422	1437			
3 Lines	β est.	0.128	0.086	0.118	0.067	1871
	AIC	2088	2140	2078	2145	
	SIC	2094	2146	2089	2156	
4 Lines	β est.	0.115	0.076	0.121	0.084	1826
	AIC	2718	2801	2709	2820	
	SIC	2723	2807	2726	2837	
5 Lines	β est.	0.110	0.108	0.113	0.116	1780
	AIC	3181	3383	3186	3282	
	SIC	3186	3389	3208	3304	
6 Lines	β est.	0.094	0.062	0.070	0.046	1780
	AIC	3775	3808	3613	3684	
	SIC	3780	3813	3641	3711	

We provide the estimates of β, the Akaike Information Criterion (AIC, Akaike, 1974) and the Schwarz Information Criterion (SIC) 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 SIC, every value for the Conditional Logit model (1) is lower than that for the Multinomial Probit 1 model (2). Additionally for both measures, every value for the HEV model (3) is lower than that for the 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 for for the data 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
	SIC	1435	1430			
3 Lines	AIC	2116	2154	2087	2154	1871
	SIC	2116	2154	2093	2160	
4 Lines	AIC	2729	2903	2722	2810	1826
	SIC	2729	2903	2733	2821	
5 Lines	AIC	3186	3317	3190	3241	1780
	SIC	3186	3317	3207	3257	
6 Lines	AIC	3776	4153	3691	4097	1780
	SIC	3776	4153	3713	4119	

We provide the Akaike Information Criterion (AIC, Akaike, 1974) and the Schwarz Information Criterion (SIC) 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 SIC 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 SIC 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 better than the assumption that the errors have a normal distribution.

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5 Appendix

5.1 More analysis 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 analysis is otherwise identical to those in Table 6. We summarize these tobit regressions in Table A???.

Table A???? 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 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 negative. This implies that choices are worse in the high cognitive load treatment.

5.2 More analysis on the quality of searches

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

Table A???? 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 problem implies that the number of unique lines are 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 clicked on during a trial. This analysis is summarized in Table A???.

Table A???? 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 A????, we see evidence that 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. We conduct the analysis as above, but with the variable *Line lengths weighted by time*, defined to be the average of the line lengths viewed weighted by the fraction of the trial it was viewed. This is summarized in Table A???.

Table A???? 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 average of the length of the lines viewed, weighted by time, is significantly smaller than those in the low cognitive load treatment. Again, we find evidence that subjects in the high cognitive load treatment conduct worse searches.

5.3 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 A???.

Table A???? 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 negative. This implies that choices are worse in the high cognitive load treatment.