“Not Worth the Effort”

Cognitive Load and Suboptimal Behavior

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Abstract

Traditional expected utility models do not allow cognitive load to influence economic behavior. However, dual-self models of impulse control predict that states of high cognitive load lead to suboptimal outcomes. This paper develops a model which captures the comparative statics of dual-self models while also keeping the familiarity of the standard expected utility model. The predictions of the model are tested in a laboratory experiment. The results suggest that, consistent with the model, subjects perform worse under high cognitive load than low cognitive load, and that increases to reward do not mitigate the effects of cognitive load. The results also show that subjects value their effort in a manner consistent with the model, though those under higher cognitive load are less sensitive to the strength of a suggestion than those in a state of low cognitive load. Order effects are found in both performance and willingness-to-pay for suggestion experiments, suggesting that effort levels are reference dependent.

JEL Codes: C91, C50, D83, D84

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1 Introduction

Consider the common expression "it is not worth the effort". One sentiment that the phrase can express is that the cost of mental effort necessary to complete some task is greater than the utility the completed task is expected to return. This style of thinking is often described as standard cost-benefit analysis, which makes up the core of most economic modeling in expected utility maximization. For example, let us consider a familiar experience: visiting a supermarket. We can imagine entering the store with a list of its items, their value to us, and their respective prices. Given that we face a budget constraint, there exists a non-trivial bundle of items that gives us the greatest utility. The optimal bundle might not require much mental effort to calculate when the item list is small, but longer lists will increase the cognitive difficulty, or cognitive load. We could create a new model which introduces these mental effort costs and attempt to solve for an optimal level of effort. Doing so would paradoxically require us to expend mental effort to calculate an optimal level of mental effort, and it can be seen that the process of creating new models to pick an optimal level of mental effort could iterate ad nauseum.

The question of how costly mental effort is to an individual is interesting and under-explored in the literature. A likely reason is that the cost of mental effort is private and subjective, unlike many traditional settings where we consider goods that have publicly known prices. Further, the task that effort is directed toward and the abilities of an agent heavily influence the cost of effort, leading to heterogeneous effects across individuals. So far no paper has attempted to find a mechanism to identify an agent's exact value of mental effort or compared such a measure to the actual performance of an individual in a task.

This paper introduces a meta-model which operationalizes effort and cognitive load in the setting of an expected utility model. The word "meta" is emphasized and used to refer to the fact that the model considers solving a secondary model and the costs associated with solving the secondary model. Put differently, the meta model studies how much effort an agent will devote to solving the original model. The meta-model is designed to capture the comparative statics of the dual-self models (Fudenberg & Levine 2006, Mukherjee 2010) as well as keeping the familiarity and simplicity of the expected utility model. The model is then cast in such a way that propositions regarding the agent's willingness to pay for effort reducing suggestions can be generated. Crucially, the meta-model predicts that increases in cognitive load lead to: 1) decreases in optimal effort and 2) increases in the willingness to pay for effort reducing suggestions. The model also allows for the study of how reward influences effort. The model predicts that optimal effort will rise and willingness to pay for suggestions will fall when considering increases in piece-rate rewards.

The meta-model predictions are tested in the context of a novel, real effort task. This task allows for varying degrees of accuracy so that subjects may opt to perform "sub-optimally" and still receive payment. The experiment uses standard digit memorization tasks in order to manipulate cognitive load levels and a novel use of the Becker-DeGroot-Marschak elicitation to evaluate the price of effort in real effort games. Both the cognitive load and piece-rate rewards are varied to examine their effects on willingness to pay for suggestions as well as on performance when suggestions are not present.

The results of the experiment support that the model's predictions with regard to performance and the price of effort under low and high levels of cognitive load. The effect of high reward is seen when we examine WTP for suggestions, but not in performance. The interaction effect of high cognitive load and high reward is seldom significant, which is also consistent with the model. The order in which subjects proceed through the different treatments also affects subject's performance and subjective valuation of effort. This study establishes that order effects may be the result of reference dependence, and that treatment orders significantly condition subjects to behave in certain, predictable ways when they encounter changes in cognitive load and reward states.

Cognitive load theory makes a connection between the actions that agents may take and the amount of cognitive resources the agent has at their disposal, especially short term memory (Sweller 2003, Sweller & Sweller 2006). The cognitive load literature originally developed to understand how new teaching methods could be designed to decrease the cognitive burden placed on a student when being taught new material. Cognitive load has been featured in dual-self theories of decision making (Fudenberg & Levine 2006, Mukherjee 2010). These models typically seek to formalize concepts similar to Daniel Kahneman's fast and slow reasoning systems that an agent possesses, and in particular it formalizes the cost of impulse control (Kahneman 2011). In other words, the model associates a cost with choosing a better long term outcome instead of an impulsive short term outcome. In Fudenberg & Levine (2006), cognitive load is incorporated into the model, which serves to increase the cost of self control.

In addition to dual-self models, there is also a rich literature on axiomatic costly choice theories. Within the choice deferral literature there is a notion that agents may not instantly know what their choice from a menu of alternatives would be and would prefer to defer their decision to a future period (Costa-Gomes et al. 2014). This is done in order to learn more about the menu and the alternatives within it so that learning can occur and a best choice can be obtained. In a similar manner, agents might value deferring a decision on how much effort to exert until they become more familiar with the task at hand.

Others model the size of the menu sets as disutilities, as in the thinking aversion literature (Ortoleva 2013), the disutility arising from costly preference or taste formation (Ergin & Sarver 2010), or as the result of choice fatigue (Fudenberg & Strzalecki 2015). Each of these suggest that there is a mental price to be paid by an agent during the decision making process and that this price, in some cases, may be prohibitively high so as to preclude the optimal choice being chosen from a menu of alternatives.

In the experimental literature, cognitive load has been shown to affect many areas of decision making (Deck & Jahedi 2015). In laboratory experiments, subjects are shown to perceive probabilities less objectively (Sprenger et al. 2011), increase risk averse behavior (Benjamin et al. 2013), and reduce strategic sophistication in simultaneous move games (Duffy & Smith 2014) when under higher amounts of cognitive load. These behaviors show that agents typically deviate further from the predictions of traditional expected utility models when faced with a high and costly cognitive load.

However, still unanswered are questions relating to how cognitive load impacts performance in tasks which are not rewarded in an all-or-nothing manner and also how subjects respond to suggestions under different levels of cognitive load. It is currently unknown at what point cognitive load induces a subject to take suggestions, even uninformative ones. The value of a suggestion is driven by the opportunity cost of exerting mental effort, and an examination of the pricing of suggestions may illuminate how subjects value their mental effort. Experiments on the value of mental effort have been performed before (Westbrook et al. 2013), though never has the price of mental effort been calculated using the BDM elicitation strategy, which allows for the precise and truthful revelation of the price of mental effort. Another topic left unexplored is whether the patterns in the effects of cognitive on valuation of mental effort match those of the effects of cognitive load on actual performance. This study uses an experimental design which can speak to each of these considerations.

2 Theory

2.1 Optimal Effort

The model developed here can be used in the context of any task in which there is a single optimal solution that an agent must exert effort to find[1]. Let $V(e, r, d)$ be the total value of taking action a given effort, e, and cognitive load, d.

$$V(e, r, d) = U(a(e), r) - D(e, d) \tag{1}$$

Here, e is the level of effort that the agent chooses and $a(e)$ is the action taken when effort e is exerted. U is the utility derived from the action a and the reward level r. D is the cognitive cost from exerting effort e under cognitive load d, and V is the total value of

[1] In economic applications, we might consider the optimal allocation of income for consumption or a principal deciding what the optimal wage for a shirking agent. In both cases listed, any realistic portrayal of the agent would not feature the agent automatically jumping to the optimal solution. As academics, we are familiar with being asked to solve a model in our graduate studies. Never did anyone innately know the optimal solution. Instead, we devoted effort toward solving the model. Often times solutions were not wholly correct, producing suboptimal solutions instead of optimal ones.

taking an action under a particular cognitive load. Action a is an element of a closed and compact set A. For simplicity, it is assumed that a has a continuous support, though the action set A may be thought of as containing a finite set of elements. The effort exerted by the agent, e, will also be a number from a closed, compact set, bounded above by $\bar{e}$, the absolute maximum amount of effort an agent could conceivably expend. This set is also assumed to have an uncountably infinite number of elements. Further, it is assumed that if the effort of an agent was allowed to tend to infinity, the optimal action would be taken with certainty.

It is assumed that U is increasing and concave in e and that D is increasing in e and convex. As in many dual self theories incorporating cognitive load, U and D are assumed to be additively separable (Fudenberg & Levine 2006, Mukherjee 2010).

The objective of the agent is to pick the effort level that maximizes expected value, or mathematically,

$$a^* = a(e) = \arg\max_{e} \left[E[V(e, r, d)]\right]. \tag{2}$$

It is also assumed that an increase in cognitive load, d, increases the marginal cost of effort. Similarly, an increase in reward, r, increases the marginal utility of effort. These are both displayed in Figure 1.

The optimization problem is

$$\max_{e} E\left[U(a(e), r) - D(e, d)\right] \tag{3}$$

which admits a unique solution given by

$$\frac{\partial U(a(e^*), r)}{\partial e} - \frac{\partial D(e^*, d)}{\partial e} = 0. \tag{4}$$

The assumptions lead us to the following propositions. Proofs for these propositions can be found in the appendix.

Proposition (1.a)**.** *Ceteris paribus, an increase in cognitive load, from* d *to* d'*, leads to a decrease in optimal effort, from* e^* *to* $e^{*\prime}$.

There is an analogous proposition involving reward.

Proposition (1.b)**.** *Ceteris paribus, an increase in reward, from r to r'' leads to an increase in optimal effort, from e^* to $e^{*''}$.*

Lastly, there is a proposition regarding the *interaction* effect of simultaneous increases of cognitive load and reward.

Proposition (1.c)**.** *Ceteris paribus, for a simultaneous increase in d to d' and r to r'', the resulting e^* will have the relation $e^{*''} > e^* > e^{*'}$.*

2.2 Suggestions and the Price of Effort

In this section we consider the value of putting effort into a decision versus following a suggestion for the solution. Cases of receiving suggestions to problems under high cognitive load are numerous. One example is cheating during a test. In this setting, the difficulty of the problems create high cognitive load for the students. It is commonly observed that as the difficulty of the problems becomes greater that, ceteris peribus, a student's desire to cheat increases. In essence these students are increasing the value of a suggestion for the solution to the problems as cognitive load increases. The role of cognitive load in determining a value of suggestions does not only apply to cheating, but indeed to any situation where we might wish to leave solving a difficult problem to someone or something else.

In the new model, it is assumed that the suggestion is a draw from a uniform distribution centered around the optimal solution and with support (a, b). For simplicity, let us examine the simplest case where the agent will exert no further effort attempting to find the optimal solution after receiving the suggestion, meaning that the agent will simply use the suggestion as their action after it has been received. Under these assumptions, it is found that the value for the use of a suggestion is

$$V(a^{sug}, 0, r, d) = U(a^{sug}, 0, r) - D(0, d)$$

where a^{sug} is the suggested action and $a^{sug} \sim U(a, b)$ and $a^* = \frac{b-a}{2}$.

Here it is noted that effort e has been set to 0 in the extreme case where the agent will certainly follow the advice given to them. Since the agent is deciding whether or not to receive the suggestion before knowing the suggestion's realization, the expected value of the suggestion is

$$E\left[V(a^{sug}, 0, r, d)\right] = E\left[U(a^{sug}, 0, r) - D(0, d)\right]. \tag{5}$$

Because the second cost term, D, is known in the model, it can be removed from the expectation, giving:

$$E\left[V(a^{sug}, 0, r, d)\right] = \int_a^b U(a^{sug}, 0, r) dF a^{sug} - D(0, d) \tag{6}$$

The decision to take a suggestion in the current context then reduces to whether the value of exerting effort is higher or lower than the value of accepting a suggestion. Formally:

$$EV(e, r, d) > EV(a^{sug}, 0, r, d) \tag{7}$$

$$E\left[U(a(e^*), 0, r) - D(e^*, d)\right] > E\left[U(a^{sug}, 0, r) - D(0, d)\right] \tag{8}$$

$$EU(a(e^*), 0, r) - D(e^*, d) > EU(a^{sug}, 0, r) - D(0, d). \tag{9}$$

Since it is known that $D(e^*, d) - D(0, d) > 0$, it means that an agent will only exert effort when

$$EU(a(e^*), r) - EU(a^{sug}, r) > D(e^*, d) - D(0, d) \tag{10}$$

which says when the expected difference between the benefit of exerting optimal effort and taking a suggestion is greater than the difference between the cost of exerting optimal effort and taking a suggestion, the agent will exert optimal effort, e^*.

It is further assumed that the value function V is quasi-linear in money, m, or

$$V(m,e,r,d) = m + U(a(e),r) - D(e,d) = m + V(e,r,d) \tag{11}$$

then it can be shown that there is some value of money, m, at which the agent is indifferent between effort level e^* and accepting m. We denote this level of money m^e. This m^e would be the willingness to pay for a suggestion which is the same value as the agent would get from exerting e^* effort, or $V(e^*, r, d) = m^e$. Because we can pick values of a and b continuously and because when $a^{sug} = a^*$ the value of the suggestion is above the value of exerting effort level e^*, we can pick a and b to be values which give the value of a suggestion $EV(0, r, d) = m^e = EV(e^*, r, d)$. As $b - a$ moves closer to zero, the value of the suggestion grows and eventually exceeds m^e. Let this amount of money be called m^{sug}. Thus, when $m^{sug} > m^e$ we can find the willingness to pay for a suggestion that one would follow with certainty as $m^{sug} - m^e$.

It is also possible to determine how changes in d would affect the WTP for a suggestion.

Proposition (2.a). *Ceteris paribus, for an increase in d, the relative value of a suggestion is increasing.*

A similar result can be found for how the value of a suggestion responds to an increase in reward r.

Proposition (2.b). *Ceteris paribus, for an increase in r, the relative value of a suggestion is decreasing.*

We can combine the above propositions about the value of suggestions to show what will happen when d and r are raised simultaneously.

Proposition (2.c). *For a simultaneous increase in d and r, the resulting value of a suggestion will be less than the value of a suggestion under an increase in d alone and greater than the value of a suggestion under an increase in r alone.*

3 Experimental Design

Since the meta-model primarily involves rewards and costs of mental effort, these two parameters, r and d, are used to test the theory laid out in the previous section. The payoffs of any real effort task can be varied, and the amount of cognitive load can be varied using the digit memorization task as used in Deck & Jahedi (2015) and many others. The experiment has a 2×2 design:

Each subject progressed through the four treatments in four different predetermined orders. These four different orders were initially used to reduce order effects, and later provided insights into the reference dependent nature of cognitive load. Additionally, the experimental design allows for individual level characteristics to be controlled by using a within-subjects treatment design. Consequently, different ability levels of participants in different sessions could be ruled out as explaining differences in memorization and multiplication tasks.

In this study, two experiments were used to get at the fundamental predictions of the meta-model. The first experiment was designed to test the predictions about optimal effort that underlie the price of effort predictions. The second experiment used a novel method in which a subject can reduce cognitive load by taking a suggestion. The subject, if they wished to obtain the suggestion, participated in a Becker-DeGroot-Marschak (BDM) auction. Since the BDM mechanism incentivizes truth-telling behavior, and the suggestion also reduced the effort required to solve the problem for the subject, the bid price for a suggestion acts as a proxy for the price of a subject's mental effort. Thus the experimental method provided an estimate of the price of costly mental effort using the willingness to pay (WTP) for even a poor suggestion under different states of cognitive load and reward.

3.1 Main Task: Multiplication Task

Subjects in the multiplication task were given sixty seconds to multiply two two-digit numbers together. The numbers were generated such that the solutions to the multiplication task were always four digits in length. Subjects were paid based on the number of correct digits in their solution. The multiplication task used is similar to many found in the real effort literature, except that the version used in this experiment allows for subjects to pick "how correct" they would like to be, rather than the task being evaluated as wholly correct or incorrect. Additionally, it is empirically verified that different digits in a solution have different degrees of difficulty involved in their computation. In the context of this experiment specifically, the digits hardest to calculate arranged from hardest to easiest are hundreds, tens, thousands, and ones, meaning that the returns to mental effort were decreasing. As an example of how the task worked in practice, consider if a subject was asked to multiply the numbers 52 and 74 (which has the solution 3848) and the subject had responded with the answer of "2448". Then the subject's response would be awarded two correct digits of a possible four.

Before the multiplication task, subjects were given a memorization number to keep in their memory. They were given ten seconds to memorize their number, which was either two or seven digits in length depending on the round. The number of digits in the memorization numbers follows a convention established by other cognitive load experiments found in the review of literature in Deck & Jahedi (2016) with more digits associated with higher cognitive load. Following the multiplication task, subjects were given twenty seconds to recall their memorization number. Payment for participation in the multiplication task was dependent on the successful recollection of the memorization number - if subjects did not recall the number, then their payment for the round was $0. To properly induce cognitive load, subjects were not allowed to use pen and paper or use their cellphones and at no point could the subjects use the computer's clipboard to store memorization numbers. The combination of a memorization task and multiplication task constituted a round.

To test for the effects of changes in marginal utility, the payment from each correct digit could be either $0.75 or $1.50 (called "low reward" and "high reward" rounds respectively), depending on the round. Returning to our previous example, if subjects were asked to multiply the numbers 52 and 74 (which has the solution 3848) and the subject had responded with the answer of “2448” and the subject were in a high reward round, they would earn $3.00 for their two correct digits conditional on correctly recalling their memorization number. Subjects were always notified when a change in reward was occurring.

3.1.1 Price of Effort

In experiments that examined the price of effort, before the multiplication task was given, subjects took part in a Becker-DeGroot-Maschak lottery, in which subjects bid to win a suggestion. Subjects were given 15 seconds to make bids for the suggestion. Subjects were told to enter a number between zero and one hundred, which represented two things simultaneously. First, it represented the likelihood that their bid was successful, with each unit increase in their bid also increasing the percentage chance that they won the suggestion by one percent. Second, the number represented what percentage of their earnings would be forfeited if their bid was successful. If a subject won the suggestion, the suggested solution was displayed to the subject during the multiplication task. It was to the subject’s discretion whether or not to use the suggestion or how much of the suggestion would be used in their final solution.

The program calculated answers to the multiplication task in a stochastic manner. First, a number of digits were specified to be incorrect, and this number ranged from 0 to 3. Therefore, at maximum, 3 digits in a suggestion could be incorrect and at a minimum 0 digits were incorrect, indicating the suggestion was perfectly informative. Then the computer determined how many of the possibly incorrect digits would be incorrect in that round at random. Subjects were not told how many digits were incorrect. As the number of digits that possibly could be incorrect was increased, the signal becomes noisier, producing worse suggestions in expectation. Subjects were always informed how many digits were possibly incorrect before a round started and during bidding for the suggestion.

A depiction of the timing of events during the experiment can be found below.

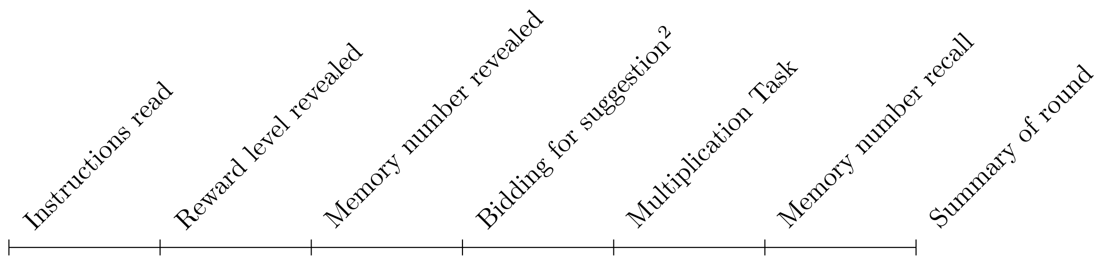

Figure 1: Timeline of events in experiment

3.1.2 Deviations from Optimal Behavior: Hypotheses

Hypothesis (1.a)**.** *When cognitive load is increased from the low cognitive load treatments to the high cognitive load treatments, the deviation from optimal behavior (in the expected utility sense) will increase, all else held equal.*

Hypothesis (1.b)**.** *When the reward from optimally solving a task is raised from the low reward treatments to the high reward treatments, the deviations from optimal behavior (in the expected utility sense) will decrease, all else held equal.*

Hypothesis (1.c)**.** *When cognitive load and reward from optimally solving a task are both raised from low levels to high levels in the H/H treatment, the deviations from optimal behavior (in the expected utility sense) will be between those of the H/L and L/H treatments.*

3.1.3 Price of Effort: Hypotheses

The model makes the following predictions of the subjects' behavior.

Hypothesis (2.a)**.** *When cognitive load is increased from the low cognitive load treatments to the high cognitive load treatments, the price paid for a suggestion will increase, all else held equal.*

Hypothesis (2.b)**.** *When the reward from optimally solving a task is raised from the low reward treatments to the high reward treatments, the price paid for a suggestion with decrease, all else held equal.*

Hypothesis (2.c). *When cognitive load and reward from optimally solving a game are both raised from low levels to high levels in the H/H treatment, the price paid for a suggestion should be between those of the H/L and L/H treatments.*

3.1.4 Subjects, Sessions, and Earnings

During a session subjects participated in sixteen rounds, four rounds from each of the four treatments. In total, eighteen sessions were conducted at the University of California, Irvine's Experimental Social Science Laboratory between. Eleven of these sessions were for the experiment with suggestions and seven were for the experiment without suggestions.

The entirety of the experiment was carried out on computer terminals using zTree (Fischbacher 2007). Subjects participated in 16 multiplication tasks, 4 in the L/L treatment, 4 in the H/L treatment, 4 in the L/H treatment, and 4 in the H/H treatment. At the end of the experiment, one high reward round and one low reward round were chosen randomly for payment. Finally, subjects completed a short demographic survey.

Fifty-eight students participated in the price of effort experiment and the average earnings were \$13.31 per subject. Eighty-nine students participated in the non-price of effort elicitation experiment and the average earnings were \$13.46 per subject. Sessions lasted roughly 45 minutes from beginning of instruction to the completion of the experiment for the experiment with suggestions and 30 minutes for the experiment without suggestions. The demographic breakdown of the subject sample is shown in the table below.

4 Experimental Results

4.1 Experiment 1: Performance without Suggestions

Table 1 provides statistics on relevant outcome variables between the four different treatment types in the experiment without suggestions.

There are a few patterns worth discussing from Table 1. In statistics related to the memorization and multiplication task, the effect of heightened cognitive load is present while the effect of increased reward seems is negligible. To control for confounding factors arising from subject specific characteristics and learning over time, I turn to regression analysis, shown in Table 2. Since the treatment variable is independent of unobservable subject level characteristics, a random effects model is used. The column header indicates the dependent variable which is regressed on the treatment variables along with a time trend to account for learning effects with robust standard errors clustered at the subject level. I use G*Power 3's post hoc power analysis for multiple regression (Faul et al. 2007) to determine that the power of these analyses are all above 0.95, with most achieving a power of nearly 1.

There may be correlation between whether or not a subject's recall is correct and the correctness of their answer. To address these concerns, we look at performance in the multiplication task when subjects correctly and incorrectly recall the memorization number. These results are displayed in Tables 3 and 4. These analyses are identical to those done in Table 2, only changing the sample under consideration.

As a robustness check, Table 5 uses MLE estimators for the above regressions where appropriate. Logit models are used for the correct recall of the memorization number, because correct recall is a binary variable. Since the percentage of digits correctly calculated in the multiplication task can take only four values, an ordered logit model is used. The same technique is used for the number of digits attempted models. As in Table 2, the column header indicates the dependent variable which is regressed on the treatment variables along with subject and period fixed effects with robust standard errors clustered at the subject level.

Finding (1.a)**.** *Consistent with the model, increasing cognitive load significantly decreases the likelihood of correct recall and performance in the multiplication task.*

As can be seen in Tables 2 through 5, regardless of model specification, the effect from high cognitive load on correct recall is negative, large, and significant ($p < .01$), which indicates that the memorization task with seven digits is significantly harder than the memorization task with only two digits and can properly be thought of as putting the subjects into a state of high cognitive load. However, higher cognitive load *positively* affects the percent of correct digits in the multiplication task at a marginally significant level ($p < .05$). This effect is measured not only in the correctness of the solution, but also in the number of digits attempted and similar measures.

Finding (1.b)**.** *Inconsistent with the model, increased reward has an insignificant impact on correct digits in the multiplication task and correct recall.*

Tables 2 through 5 report the effects of reward on correct recall and measures of performance in the multiplication task. In no table is the high reward dummy variable significant, counter to the predictions of the model. A power analysis revealed that in order for the size of the effect associated with reward to be considered significant the sample size would need to be nearly $120,000$. A detailed version of the analysis is included in the appendix. This further indicates that increased reward cannot offset the persistent negative effect of cognitive load found above in any significant way.

Finding (1.c)**.** *Consistent with the model, the interaction effect between high cognitive load and high reward is insignificant in both the memorization and multiplication task, except in the case of number of digits attempted.*

The theory predicts that, since cognitive load and reward enter the value function additively, there should be no interaction effect between cognitive load and piece-rate reward. The results from Tables 2 and 5 make clear that the interaction effect never significantly is different from zero, consistent with the theory. This indicates the model's additivity assumption is reasonable.

4.1.1 Order Effects

Tables 6 to 10 explore the role of order effects and reference dependent attitudes to effort and cognitive load. I use G*Power 3's post hoc power analysis for multiple regression to determine that the power of these analyses are all above 0.94, with most achieving a power of nearly 1. What is evident is that the effects of cognitive load, reward, and their interaction are more nuanced than what is indicated in Tables 1 through 5. Most effects found in these tables can be seen clearly in Table 6. The four orders are summarized in Figure 3. Average performance by order can be found in Figure 4.

A few results to note are that subjects in certain orders had higher levels of performance than others outcomes by others by a significant margin and that certain orders responded differently to cognitive load than others. Figure 4 shows that there are significant differences in performance between the four different orders. Using Kolmogorov-Smirnov tests, orders 1 and 4 perform at a significantly higher level than orders 2 and 3 ($p < 0.01$), though orders 2 and 3 are not significantly different from each other.

Not only do the different orders have distinctive differences in performance, but subjects in some of the orders have features not shared by the others. Figure 3 shows that subjects in orders 3 and 4 begin with either two consecutive treatments of low cognitive load or high cognitive load. What is more, Table 6 shows that subjects in these two orders have negative and significant ($p < 0.05$) responses to increased cognitive load. Tables 7 through 10 show this pattern as well in the form of pooled regressions. It is clear that the order of treatments can affect how subjects respond to the treatment variables.

Also shown in Tables 6 and 7 is that subjects in different orders are affected by the interaction of high cognitive load and high reward. These effects are not observed in the aggregate. In the case of subjects who begin in the H/L treatment, the interaction has a significant ($p < 0.01$) and positive effect, while those who began in H/H have an interaction effect that is significant ($p < 0.01$) and negative.

4.2 Experiment 2: Price of Effort

Table 12 shows summary statistics of relevant outcome variables between the four different treatment types.

Also visible in the final row of Table 12 is that the mean price of the bids for suggestions follow the pattern predicted by the model. Relative to the low cognitive load/low reward treatment, an increase in cognitive load alone raises the WTP for a suggestion. Similarly, an increase in reward alone lowers the WTP for a suggestion. Raising cognitive load and reward to a high state simultaneously moves the WTP for a suggestion in between the high cognitive load/low reward WTP and the low cognitive load/high reward WTP. All three of these predictions are made by the model. A random effects panel data model is used to control for the subject specific effects, learning effects, and other individual level effects. Table 13 reports these estimates.

It may be the case that there is correlation between whether or not a subject's recall is correct and a subject's WTP for a suggestion. Therefore performance in the multiplication task is broken down by those who correctly recalled and those who did not correctly recall the number in the memorization task.

Additionally, Table 14 shows the effects of the treatment variables when the suggestions are of different strengths. The program generate random numbers that represented a certain number of coin tosses, and the coins that landed as heads determined how many digits in a suggestion were incorrect. As stated above, there were four different strengths of suggestions, 3 flips, 2 flips, 1 flip, and 0 flips, with 3 flips being the least informative of suggestions and 0 flips being perfectly informative. The results show the same treatment effects as were shown before and the constant terms should reveal the trend in the average prices of bids over the different qualities of suggestions. The WTP under different levels of noise in the suggestions provides a rationality check on the subjects.

Table 15 shows a breakdown of the effects of the treatment variables on WTP for a suggestion conditional on the order the subjects encountered the treatments. It was previously established that the order effects can play a roll when subjects decide how much effort to allocate to the multiplication tasks and the same is true when considering WTP for suggestions. Table 16 shows a pooled version of these regressions, allowing for the estimation of the direct order effect. I use G*Power 3's post hoc power analysis for multiple regression to find that the pooled analysis ignoring the effects of order is 0.85, while those that include it achieve a power of 0.95.

Finding (2.a)**.** *Consistent with the model, there is evidence that subjects pay more for suggestions when cognitive load increases. This is especially evident when observing effects conditional on orders.*

As discussed earlier, the unconditional means of the treatment effects show that higher cognitive load alone raises the WTP for a suggestion in subjects, though this effect is not immediately recognizable until we condition on order effects. Table 15 and 16 show how WTP for suggestions responds to changes in cognitive load after order effects are taken into consideration. In the two cases where the effect from cognitive load is significant, it is large and positive ($p < .01, p < .05$). These results are in line with the model.

Finding (2.b)**.** *Consistent wit the model, there is evidence that subjects have a lower WTP for suggestions when reward increases. This effect is made more evident when controlling for order effects.*

Table 6 suggests that the unconditional means of the treatment effects for higher reward alone decrease the WTP for suggestions in subjects, though the result is initially insignificant until we take a more detailed look at how subjects in different orders responded. In two of the three cases in which the effect of high reward has a significant ($p < .05$) impact on WTP for suggestions the estimate is negative, which is in line with the predictions of the model. The one case in which the estimate is positive and significant ($p < .050$) are for those subjects of order 4, those who began in the high cognitive load/high reward treatment.

Finding (2.c)**.** *Consistent with the model, there is evidence that when subjects are in a state of high cognitive load and high reward simultaneously, their WTP for a suggestion is above the WTP for a suggestion in a high cognitive load/low reward state and below the WTP for as suggestion in a low cognitive state/high reward state.*

As with the predictions of the model with regard to the interaction effect of high cognitive load and high reward on performance, the interaction effect should produce zero effect on the WTP for suggestions due to the additive nature of the terms. Tables 13 through 16 show that nowhere does the interaction effect significantly affect the WTP for suggestions. A power analysis revealed that in order for the size of the effect associated with reward to be considered significant the sample size would need to be nearly $130,000$. A detailed version of the analysis is included in the appendix. What is more, the average

WTP for suggestions in the H/H treatment lies between those of the H/L and L/H treatments, which is consistent with the model. This result holds even when breaking down results by the order in which subjects encountered the different treatments.

One result that was not initially hypothesized, but is nonetheless substantial, is that subjects have a harder time analyzing the objective value of a suggestion in a high cognitive load state than in a low cognitive load state. It should be the case that as the quality of a suggestion decreases (increases), then the WTP for that suggestion also decreases (increases). What is seen in Figure 2.7 is that this pattern is found in subjects under the low cognitive load treatment, but that this pattern is muted in the high cognitive load treatment. Thus we can see that a subject's sensitivity to the quality of a suggestion is diminished by increased cognitive load.

5 Discussion

The model is consistent with many of the results of the experiment. For predictions made with regard to performance, it is found that high cognitive load has a significant and negative effect and that the interaction of high cognitive load and high reward has an insignificant effect, both in line with the model's predictions. The only prediction that is not supported is that reward should always boost performance, which it does not. This suggests that there may not be a cost-benefit analysis made by agents when it comes to the activation of fast or slow-thinking systems.

Similarly, the model does a good job in predicting subjects' WTP for suggestions after order effects are controlled for. For multiple groups, the model predicts that the WTP for suggestions rises under higher cognitive load, falls under raised reward, and is not significantly impacted by the interaction of these two effects, all of which are predictions of the model. These results are originally obscured by order effects arising from the different orders of treatments that subjects faced.

From the results, it is clear that cognitive load affects our deliberative effort. From Figure 3 and Tables 6, it was shown that two groups had the lowest performance - those whose first two consecutive treatments were either high or low cognitive load without alternation. In the case of those who started purely with high cognitive load treatments, decision fatigue may have played a role (Baumeister 2003, Twenge et al. 2000). For these subjects, the mentally taxing tasks were all front loaded, which may have left them with depleted cognitive resources later on in the experiment, causing larger errors. For those that started with two treatments in low cognitive load states, a reference point for low effort may have been set. When one starts with a reference point of needing little effort to reap large rewards, it can lead to aversion to supplying larger amounts of effort to capture those same rewards later on in the experiment. It is interesting to note that these effects are not found where low and high cognitive load treatments alternate over consecutive treatments, suggesting that fatigue can be ameliorated by alternation between more and less challenging tasks and that reference points for effort levels may not have time to form when the conditions of the task are changing more rapidly.

Another interesting result is found in Table 7. It can be seen in Tables 2 through 5 that the interaction effect between high cognitive load and high reward does not seem to play a roll, but Table 7 reveals that subjects in two different orders had their performance helped or hindered as a result of the interaction effect. Interestingly these two orders both started in high cognitive load treatments with the difference being that order 2 subjects started in the H/L treatment and order 4 subjects started in the H/H treatment. It is likely that those who began in the H/H treatment had not yet had a chance to adapt to the effort required of them in the first four rounds, and thus their performance suffered the most in this treatment. Alternatively, for those starting in the H/L treatment, these subjects became acclimated to the effort required under high cognitive load in the first four periods and performed better when they arrived in the H/H treatment for the next four rounds. This experiment makes clear that the ordering of cognitively taxing tasks has an effect on performance that should be investigated further.

Similar to performance, order effects are important to consider when we thing about subjective valuations of the price of effort. Before investigating how the different orders responded to changes in cognitive load and reward, the unconditional estimates show that WTP for suggestions is not greatly affected by either. However, in a more detailed analysis, it can be seen that subjects in most of the orderings can correctly anticipate the effect cognitive load and reward will have on the value of their effort and place a bid that will enhance their payoff. These results are directly in line with the predictions of the model.

We also note that those who began in high cognitive load treatments bid significantly less than those who began in low cognitive load treatments. This is likely because those in the high cognitive load treatments formed expectations about how much their effort was worth under conditions of high cognitive load, and, on average, anticipated their effort to be worth more than their low cognitive load counterparts. Put differently, when one begins in a state of high cognitive load, one tends to acclimate to these conditions and find it a pleasant surprise when they encounter the low cognitive load treatments. Supporting this notion is the fact that across all orders, their is no significant difference in WTP for suggestions in the in the first four rounds (constituting the first treatment the subjects encountered), but that those who began in high cognitive load treatments began to bid less in low cognitive load states than those who started in low cognitive load treatments. This can be seen in Figure 5.

It may also be the case that asking for bids for suggestions may have changed cognitive load. Asking for a bid may have increased cognitive load in a state where cognitive load was already high and made it difficult to accurately assess the value of ones effort. It is possible that asking for bids at different times during the experiment may have produced different bids for suggestions, and that the pattern of treatment effects may have looked different. However, the current paper examines how subjects would respond to suggestions during a period of high cognitive load. The timing of the bidding for suggestions is largely motivated by the real world where people are forced to make decisions about what their effort is worth while under different levels of stress.

5.1 Choice Deferral

There is some connection between the literature of cognitive load and choice deferral. The choice deferral literature seeks to explain why some people will not choose an item from a menu and instead wait until a later time to make a choice from the same menu. Some theorized reasons given by Costa-Gomes et al. (2016) are that agents may wish to wait in order to gain more information to make a best choice or that initially agents may not have complete preferences and may need time in order to complete them. In laboratory experiments subjects will often defer their decision, even at a cost.

This can been seen as comparable to the current paper, as those who take a suggestion may be doing so to defer the choice of how much effort to exert by purchasing a suggestion. This is to say that the subjects in my experiment may have exhibited a high degree of uncertainty in the first rounds of each treatment exactly how much effort to exert on the task, and may have therefore bid on a suggestion in order to earn something the first period while using the information gained about the task in the early rounds to help determine how much effort to expend in future rounds. As in Costa-Gomes et al. (2016), we would expect to see bids for suggestions decreasing over time in response to updating priors about how much effort is required for the real effort tasks the subjects performed. Indeed this is what is found in both Figure 7, which shows that over time bids shrink as subjects learn more about what effort they would like to exert. Table 13 shows the effect of period is significant ($p < 0.01$) and negative in the aggregate, consistent with effort choice deferral decisions.

6 Conclusion

In this paper we create a model for real effort selection under different levels of cognitive load. This model operationalizes some notions of how much we expect an agent to optimize in response to the cognitive load of the task as well as the reward associated with the task. We expect that the price of optimization should rise when cognitive load increases and that the price of optimization price should decrease when reward is increased. In the first case, higher cognitive load should lead to lower performance resulting from reduced effort, and in the second higher reward should lead to higher performance from increased effort. Both these effects are relative to some state of lower cognitive load and lower reward.

Findings of the experiment largely confirm the predictions made by the model. Cognitive load is found to drive down performance significantly, though increased reward does not change performance in the multiplication task using any measure. The interaction effect between high cognitive load and high reward at the aggregate level is insignificant, but the effect seems to be heterogeneous across the groups of subjects that proceeded through the treatments in different orders. For one of the orders, the effect was negative, and the other was positive. Those who experienced a negative effect started in the H/H treatment and likely failed to fully acclimate to the effort required to perform well in the high cognitive load treatment. For subjects in the other order, the effect was positive, which may be the result of subjects beginning in the H/L treatment and acclimating to the effort required under high cognitive load.

The model is similarly confirmed when we turn to the price of effort, though only after we condition on the order effects. Cognitive load has a large positive effect on the WTP for suggestions for many of the orders and reward has a large negative effect from many of the orders. These results are in line with the model, though the model makes no predictions about why order should have a role or that different orders of treatments will be associated with different average levels of bids. Again, order is found to be a strong determinant of behavior with those who begin in low cognitive load treatments on average bidding significantly higher amounts for suggestions than those who start in high cognitive load treatments, indicating those that those who begin by doing the hardest work acclimate to it, while those who do the easiest find it harder to transition to difficult work and will pay much more for assistance. Further research must be done to more fully understand the role of reference dependence on the setting of effort levels.

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References

Ariely, Dan, et al. "Large stakes and big mistakes." *The Review of Economic Studies* 76.2 (2009): 451-469.

Baumeister, R. F. and Twenge, J. M. 2003. The Social Self. Handbook of Psychology. Three:14:327–352.

Benjamin, Daniel J., Sebastian A. Brown, and Jesse M. Shapiro. "Who is 'behavioral'? Cognitive ability and anomalous preferences." *Journal of the European Economic Association* 11.6 (2013): 1231-1255.

Camerer, Colin F., and Robin M. Hogarth. "The effects of financial incentives in experiments: A review and capital-labor-production framework." *Journal of Risk and Uncertainty* 19.1-3 (1999): 7-42.

Camerer, Colin, George Loewenstein, and Drazen Prelec. "Neuroeconomics: How neuroscience can inform economics." *Journal of Economic Literature* 43.1 (2005): 9-64.

Costa-Gomes, Miguel, Carlos Cueva, and Georgios Gerasimou. "Choice, deferral and consistency." (2014).

Deck, Cary, and Salar Jahedi. "The effect of cognitive load on economic decision making: A survey and new experiments." *European Economic Review* 78 (2015): 97-119.

Ergin, Haluk, and Todd Sarver. "A unique costly contemplation representation." Econometrica 78.4 (2010): 1285-1339.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). "G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences." Behavior Research Methods, 39, 175-191.

Fischbacher, Urs. "z-Tree: Zurich toolbox for ready-made economic experiments." *Experimental Economics* 10.2 (2007): 171-178.

Fudenberg, Drew, and David K. Levine. "A dual-self model of impulse control." *The American Economic Review* (2006): 1449-1476.

Fudenberg, Drew, and Tomasz Strzalecki. "Dynamic logit with choice aversion." Econometrica 83.2 (2015): 651-691.

Getz, Sarah Jean. "Cognitive Control and Intertemporal Choice: The Role of Cognitive Control in Impulsive Decision Making." (2013).

Gino, Francesca, and Don A. Moore. "Effects of task difficulty on use of advice." *Journal of Behavioral Decision Making* 20.1 (2007): 21-35.

Hauge, Karen Evelyn, et al. “Keeping others in our mind or in our heart? Distribution games under cognitive load.” *Experimental Economics* (2014): 1-15.

Kahneman, Daniel. *Thinking, Fast and Slow.* Macmillan, 2011.

Langer, Ellen J., and Lois G. Imber. “When practice makes imperfect: debilitating effects of overlearning.” *Journal of Personality and Social Psychology* 37.11 (1979): 2014.

Mukherjee, Kanchan. “A dual system model of preferences under risk.” *Psychological Review* 117.1 (2010): 243.

Ortoleva, Pietro. “The price of flexibility: Towards a theory of thinking aversion.” Journal of Economic Theory 148.3 (2013): 903-934.

Paas, Fred, et al. “Cognitive load measurement as a means to advance cognitive load theory.” *Educational Psychologist* 38.1 (2003): 63-71.

Paas, Fred, Alexander Renkl, and John Sweller. “Cognitive load theory and instructional design: Recent developments.” *Educational Psychologist* 38.1 (2003): 1-4.

Shah, Anuj K., Sendhil Mullainathan, and Eldar Shafir. “Some consequences of having too little.” *Science* 338.6107 (2012): 682-685.

Sweller, John, and Susan Sweller. “Natural information processing systems.” *Evolutionary Psychology* 4.1 (2006).

Vohs, Kathleen D., et al. ”Making choices impairs subsequent self-control: a limited-resource account of decision making, self-regulation, and active initiative.” (2014): 19.

Westbrook, Andrew, Daria Kester, and Todd S. Braver. "What is the subjective cost of cognitive effort? Load, trait, and aging effects revealed by economic preference." *PLoS One* 8.7 (2013): e68210.

Appendix

7 Propositions

Proposition (1.a)**.** *An increase in cognitive load d leads to a decrease in optimal effort e^*.*

Proof. We have defined $V(e,r,d) = U(a(e),r) - D(e,d)$. Taking first order conditions to find e^* we get.

$$\frac{\partial V(e^*,r,d)}{\partial e} = \frac{\partial U(a(e^*),r)}{\partial e} - \frac{\partial D(e^*,d)}{\partial e} = 0$$

Thus the change in e^* with respect to d is defined as

$$\frac{de^*}{dd} = -\frac{\frac{\partial^2 V(e^*,r)}{\partial d \partial e}}{\frac{\partial^2 V(e^*,r,d)}{\partial e^2}}$$

Because $\frac{\partial^2 V(e^*,r,d}{\partial d \partial e} = -\frac{\partial^2 D(e^*,d}{\partial d \partial e}$ and we know that d increases the marginal cost of effort and that V is concave, then

$$\frac{de^*}{dd} = \frac{\frac{\partial^2 D(e^*,d)}{\partial d \partial e}}{\frac{\partial^2 V(e^*,r,d)}{\partial e^2}} < 0$$

□

Proposition (1.b)**.** *An increase in reward r leads to an increase in optimal effort e^*.*

Proof. We have defined $V(e,r,d) = U(a(e),r) - D(e,d)$. Taking first order conditions to find e^* we get.

$$\frac{\partial V(e^*,r,d)}{\partial e} = \frac{\partial U(a(e^*),r)}{\partial e} - \frac{\partial D(e^*,d)}{\partial e} = 0$$

Thus the change in e^* with respect to d is defined as

$$\frac{de^*}{dd} = -\frac{\frac{\partial^2 V(e^*,r)}{\partial r \partial e}}{\frac{\partial^2 V(e^*,r,d)}{\partial e^2}}$$

Because $\frac{\partial^2 V(e^*,r,d}{\partial r \partial e} = \frac{\partial^2 U(e^*,r}{\partial r \partial e}$ and we know that r increases the marginal utility of effort and that V is concave, then

$$\frac{de^*}{dd} = -\frac{\frac{\partial^2 U(e^*,r)}{\partial r \partial e}}{\frac{\partial^2 V(e^*,r,d)}{\partial e^2}} > 0$$

□

Proposition (1.c)**.** *For a simultaneous increase in d and r, the resulting e* will be greater than the equilibrium effort under an increase in d alone and lower than the equilibrium effort under an increase in r alone.*

Proposition (2.a)**.** *For an increase in d, the relative value of a suggestion is increasing.*

Proof. The relative value of a suggestion is defined to be $V(a^{sug}, 0, d, r) - V(e^*, d, r)$. To find how the relative value of a suggestion will respond to a change in d, differentiate to find

$$\frac{-\partial D(0,d)}{\partial d} - \left(\frac{\partial U(e^*,r) - D(e^*,d)}{\partial e}\frac{\partial e^*}{\partial d} - \frac{\partial D(e^*,d)}{\partial d}\right)$$

which can be reduced to

$$\frac{\partial D(e^*,d) - D(0,d)}{\partial d} - \frac{\partial V(e^*,r,d)}{\partial e}\frac{\partial e^*}{\partial d} > 0$$

□

Proposition (2.b)**.** *For an increase in r, the relative value of a suggestion is decreasing.*

Proof. The relative value of a suggestion is defined to be $V(a^{sug}, 0, d, r) - V(e^*, d, r)$. To find how the relative value of a suggestion will respond to a change in r, differentiate to find

$$\frac{\partial U(a^{sug},0,r)}{\partial r} - \left(\frac{\partial U(e^*,r) - D(e^*,d)}{\partial e}\frac{\partial e^*}{\partial r} + \frac{\partial U(e^*,r)}{\partial r}\right)$$

which can be reduced to

$$\frac{\partial U(a^{sug},0,r)-U(e^*,r)}{\partial r}-\frac{\partial V(e^*,r,d)}{\partial e}\frac{\partial e^*}{\partial r}<0$$

$\square$

Proposition (2.c)**.** *For a simultaneous increase in d and r, the resulting value of a suggestion will be less than the value of a suggestion under an increase in d alone and greater than the value of a suggestion under an increase in r alone.*

Proof. We know that raising d alone increases the value of a suggestion and that raising r alone lowers the value of a suggestion, therefore the combined effect must be somewhere in between these two, since there two effects do not interact. $\square$