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The Value of Knowing When to Switch: Investigating the Interaction of Value and Control

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The Value of Knowing When to Switch:

Investigating the Interaction of Value and Control

by

David Braun

A Thesis

Presented to the Graduate and Research Committee

of Lehigh University

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Master of Science

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The Value of Knowing When to Switch: Investigating the Interaction of Value and Control

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Abstract

Decisions often happen in sequence, but research in decision making tends to analyze the factors that influence decisions in isolation. A novel methodology – reward-based voluntary task switching (rVTS) – is introduced to investigate how reward, effort, and the representation of task interact with each other to influence successive task selections in a task switching environment. The present research also investigates whether the value associated with a task is integrated into the task-set representation that is used to execute a task, or whether task value is held in a separate representation altogether. Results from the present experiments suggest that people are sensitive to the amount of effort required to perform a task, and that the value of a task is not integrated into the representation of the task itself. It is possible that task value is stored in a separate representation that interacts with the representation of task to influence task selections.

Knowing the Value of When to Switch: Investigating the Interaction Between Value and Control

How do people make decisions? We decide when to get out of bed, we decide to walk to the bathroom, and we decide to brush our teeth. People make thousands of decisions each day, most of which are automatic and below conscious awareness. However, decisions can also be effortful. Deciding what house to purchase, for example, is by no means an automatic decision. Decisions can also become increasingly difficult in complex environments. Take the case of a person driving a car on a highway who is juggling between looking for road signs and watching out for erratic drivers. Depending on the situation, there might be different needs (or “values”) for looking for road signs versus attending to nearby drivers. For instance, if there are not many drivers on the highway and the destination is hard to find, it would be more valuable for the driver to focus on reading road signs. But what if an erratic driver suddenly appears or if traffic is looming ahead? It is now much more valuable for the driver to attend to nearby traffic. The driver must recognize these cues, stop focusing on road signs, and quickly avoid the erratic driver or brake for upcoming traffic. How is the driver able to monitor the values of these two tasks (i.e., focusing on road signs and watching out for traffic) and decide when to shift focus between the two?

This question is difficult to address because it involves processes that span across research domains. On one hand, the driver is faced with the choice of focusing on road signs or attending to traffic; he must determine what the values of performing these two tasks are (based on the demand for the two tasks, the effort required for the two tasks, etc.), and compare these values to make a choice between the tasks. There is evidence from the behavioral-economic literature suggesting that effort is a significant factor in the construction of preference. For example, the objective value of a task might be high (e.g., there is a large reward for performing

the task), but people will be less likely to choose this task as more effort is needed to execute it (labor supply theory; Smith & Walker, 1993). On the other hand, the driver must avoid distractions in order to focus on road signs, but he must also be able to recognize when monitoring traffic demands attention, and be able to flexibly switch his focus to the nearby drivers if the situation demands it. There is a large body of evidence from the cognitive-control literature investigating how rewards for task performance (i.e., fast and accurate task execution) can influence the mechanisms used to execute and switch between tasks (for a review, see Botvinick & Braver, 2015) – for example, people can more flexibly switch between tasks when there is a sudden increase in value for a task (Shen & Chun, 2011). In sum, there is evidence that people can assign value to options (or tasks), and there is separate evidence suggesting that value influences how well people execute and switch between tasks. How, then, does the value that people assign to tasks influence the way they choose to switch between them?

The current research aims to address this broad question by looking across research domains. I will begin by reviewing relevant evidence from both the behavioral-economic and cognitive-control domains, outlining how insight from both of these domains could be applied towards addressing integrative questions. I will then introduce a paradigm that is aptly suited to address the present research agenda: to investigate how the representation of value interacts with the representation of task to influence decision making in multitasking environments.

The Impact of Effort on Value-Based Decisions

Consider the choice between two jobs: both jobs last for one hour, and both jobs pay ten dollars. One job involves cat sitting for a friend, the other job involves picking weeds out of a disheveled garden in ninety degree weather. Which job would most people choose to perform? Even though both jobs last the same amount of time and pay the same amount of money, it is

obvious that most people would prefer cat sitting over picking weeds. People construe effort as a cost (Smith & Walker, 1993). The greater the effort that is required, the more reward (i.e., money) is needed to be willing to accept the cost. The notion of effort as a cost is so intuitive that most people would probably not hesitate in choosing to cat sit. Yet, until recently, this notion has been largely absent in the study of value-based decision making.

One of the main domains where human decision making has been studied is in the field of economics. Economic theories make specific assumptions regarding the nature of human decision making, such as the assumption that the likelihood of choosing an outcome is simply a function of the value of that outcome times the probability of obtaining the outcome (expected utility theory; Bernoulli, 1738/1954), and the assumption that preferences are stable across time and contexts (i.e., if someone prefers X to Y in context A, that person will prefer X to Y in all other contexts as well; for a review, see Rabin, 1998). However, in the 1970's, researchers began to consider the impact of psychological factors in decision making. People do not weight probabilities symmetrically, but rather are much more risk-seeking when facing potential losses and more risk-averse when facing potential gains (prospect theory; Kahneman & Tversky, 1978). Prospect theory led to the realization that preferences are not stable across contexts, but that subtle manipulations to the way a prospect is framed can drastically alter choice preferences (Ariely, Loewenstein, & Prelec, 2006; Tversky & Kahneman, 1981). For example, given two prospects with the same expected utility (i.e., the value times the probability of receiving that value is equivalent for two choices within a prospect), when the prospect is framed as a choice between (a) accepting a loss of X amount of dollars and (b) a gamble between losing less than X amount of dollars but at the risk of incurring a loss greater than X amount of dollars, people will be more likely to choose the option where there is a chance to lose less money: option b.

However, when the prospect is framed as a choice between (a) a sure gain of X amount of dollars and (b) a gamble between gaining greater than X amount of dollars but at the risk of gaining less than X amount of dollars, people will be more likely to choose the option that ensures a sure gain: option a (Tversky & Kahneman, 1981). There is much to be gained from considering the impact of psychological variables on the decision making process, and this realization was eloquently stated by Matthew Rabin in his 1998 review on psychology and economics:

The realization that many details of human behavior must be ignored, however, should not license institutionalized complacency about the behavioral validity of our assumptions; ‘tractability’ and ‘parsimony’ should be guiding principles in our efforts to make our research more realistic, not pretexts for avoiding this task. (p. 13)

Because people have an underlying desire to avoid effort (Kool, McGuire, Rosen & Botvinick, 2010), the effort that is associated with an option directly influences the process of assigning value to that option (Rangel, 2008). It follows that – in contexts where options are associated with explicit values or rewards – the amount of effort required for an option would act as a cost against the amount of reward that could be gained from that option (Smith & Walker, 1993). This is perhaps best illustrated by the opening example of this section, where the amount of effort needed to pick weeds from a garden subtracts from the ten dollar reward for performing the task. When conducting experiments investigating effort and reward in the laboratory, researchers tend to associate the most amount of reward with the task requiring the most effort (for an overview, see Smith & Walker, 1993). The most “optimal” course of action is typically defined in terms of utility maximization – a term that comes from the economic literature meaning that people should only be motivated by pursuing as much reward as possible. However, people find effort aversive (Kool et al., 2010) and are therefore motivated to balance

pursuing rewards with avoiding effort. It is for this reason that participants often fail to exhibit what experimenters consider to be “optimal” decision making in these effort-value paradigms.

The effort-value tradeoff was investigated by Kool and Botvinick (2014) over an elegant series of experiments. Participants were presented with a choice between performing a difficult and an easy task. Reward (small amount of candy) was only given for performance of the more difficult task – in fact there was no reward given for performance of the easier task. When reward for a more difficult task was commensurate with the effort required to perform that task, participants chose to perform the more laborious task about as often as they chose to perform the more leisurely task. Decreasing the reward given for the difficult task resulted in a bias against performing the more difficult task. Likewise, increasing reward for the difficult task resulted in a choice preference towards the difficult task (experiment 2; Kool & Botvinick, 2014). These results provide relatively straightforward evidence for extending the labor supply theory to cognitive effort – cognitive effort is construed as a cost, and providing monetary reward is effective in overcoming this cost. This suggests that balancing between chasing reward and avoiding effort is a function of received reward (but see Camerer & Hogarth, 1999).

The results of Kool and Botvinick’s (2014) Experiment 3 expands the labor supply theory by further investigating the relationship between reward and effort allocation. Participants were instructed to make task selections prospectively – that is, they were asked to decide how often to perform each task up front, before execution of the tasks began. This was implemented to control for the possibility that participants would only be susceptible to reward changes while under the cognitive demand of performing the tasks. Results indicated that participants’ effort allocation was not as sensitive to changes in reward when making allocations in a prospective manner as when making allocations while under cognitive load (Kool & Botvinick, 2014). This suggests

that, while mentally fatigued, people will require more compensation to do the same amount of work as opposed to when making such decisions prospectively (at mental rest). This is intriguing because it suggests that the expenditure of effort will directly influence the weighing of reward against effort to compute a decision. One interpretation of these results is that the value of effort increases as more effort is exerted; however, another possible interpretation is that people just become worse at evaluating choices between tasks as they fatigue.

One of the primary objectives of the present research agenda is to understand how the process of performing a task influences the way that people choose between tasks. For example, participants in Kool and Botvinick's (2014) study have a particular task selection strategy at the outset of the experiment (i.e., before executing the tasks, they decide how often they will perform each task). This selection strategy changes, however, once participants begin to actually execute the tasks. What influence does the process of executing a task have on the process of selecting between tasks?

An Integrative Framework of Decision Making. Within the broad field of decision making, there are theories that explain a wide variety of phenomena – from understanding how factors such as heuristics and framing shape preferences (Gigerenzer & Gaissmaier, 2011; Tversky & Kahneman, 1981), to understanding how preferences can be actively constructed during a decision (Slovic, 1991); preferences can even be constructed just by the movement of the eyes during a decision (Krajbich, Armel, & Rangel, 2010). There is also a wide range of work investigating decision making from a neuroscience perspective, for example understanding how ambiguity (Hsu, Bhatt, Adolphs, Tranel, & Camerer, 2005) and reward (Vickery, Chun, & Lee, 2011) are represented in the brain. Recently, an integrative framework of value-based decision making has been proposed that provides a means for the theories investigating these

similar, but empirically disparate, effects to merge into a cohesive whole (Rangel, Camerer, & Montague, 2008). The framework is intended to outline every stage of a decision and explain how decisions might unfold over time.

The model begins with the computing of a representation of a decision problem. People need to understand the decision they face before they can come up with ways to approach the decision. Potential courses of action are defined at this stage, as well as the development of internal goals and the identification of environmental constraints. For example, deciding what type of food to eat depends both on the level of hunger (internal) and the types of food that are available in a given context (external). This stage is followed by assigning values to the computed courses of action. It is crucial that the values computed for potential action will predict the benefits received from performing the action. The computation of value can either be generated internally or externally. A person choosing between different types of food must consider what food she likes (internal) and the prices of the available foods (external). This stage incorporates many of the behavioral economic theories of decision making, where people will weigh potential gains and costs (including effort) in systematic ways to compute action values. The next stage is the comparison of the computed values. Rangel refers to this stage as action selection, but for present purposes we will call it task selection. Once a person has assigned value to, say, two options, she must be able to compare these values to each other in order to make a decision. This is the stage where attentional processes play the largest role, and models integrating attentional processes into decision making tend to be implemented here. For example, there are models that assume that decision makers accumulate evidence for different options in making a decision, and once evidence surpasses a certain threshold, a decision can be reached (drift diffusion; Ratcliff, 1978). The desirability of the outcome from the choice is then measured

in the fourth stage, followed by the integration of the outcome in updating future decisions in the fifth stage. In other words, if a person consumed a delicious meal at a low price, this person might be more inclined to purchase this meal again in future decisions.

The framework does not explicitly account for cognitive effort being construed as a cost, but one could reasonably posit the influence of cognitive effort at various stages within the framework. Several key implications for the influence of cognitive effort on the decision-making process are found in the second and third stages of the framework, where values for the options are computed and the options are compared to make a selection.¹ Consider the value assignment stage within a context similar to the Kool and Botvinick's (2014) paradigm – where participants must choose between two tasks of differing difficulty and reward. On each trial, a participant must choose between performing an easy, low-reward task, and a hard, high-reward task. Participants must first assign a value to each task. The value assigned to these tasks is ostensibly the reward associated with the tasks. But the effort required to execute the task should factor in to the task's value as well. Just as in the cat-sitting example, the added effort required to weed a garden lowers the overall value of the task, making cat sitting the more preferable of the two options. This means that people are able to generate a representation of how much effort the choice will likely require, and weigh this abstract representation against the explicit reward that is offered by the choice. The effort required to perform an action associated with a choice can thus act as a cost when computing the value for that action (in stage two of the framework).

¹ Theoretically, each stage of the decision process could require some degree of effort, and this demand for effort could have consequences for every other stage of the decision process. However, a full discussion of these relationships is beyond the scope of the present paper. Therefore, the present discussion of the demand and the influence of effort will be constrained to the following stages of the decision process: value assignment, action selection, and execution of the task.

After assigning values to tasks, participants must compare these values to make a selection. Effort can also have an influence in the task selection process. Expending effort leads people to be more effort averse in future decisions (Kool & Botvinick, 2014). Consider two plausible explanations for this effect: as people expend more effort, they either (a) begin to value effort more, and require more reward to expend the same amount of effort, or (b) simply become worse at comparing values to make a selection. People fatigue as they expend more effort performing tasks (Belmont, Agar, & Azouvi, 2009). The latter of these two explanations assumes that fatigue will adversely affect the task selection process, the former does not. Whether or not task selection becomes worse with fatigue most likely depends on whether the task selection stage itself requires effort. If task selection is effortful, it is likely to be adversely affected when cognitive resources are being spent on task execution, which consequently leaves fewer resources available for task selection. Conversely, if task selection is automatic, it should not rely on availability of cognitive resources, and should not be affected by effort being spent on task execution. I argued above that task selection can be automatic – one does not need to deliberate to know that cat sitting is the preferable option – but this need not always be the case.

The task selection process becomes more complex as the choices become mismatched on more of their features. Take the example of comparing two food options to determine which is preferable. Comparing the price of two equally-delicious food options is relatively easy, whichever one costs less is preferable. But comparing two foods that vary in both price and deliciousness can be a more difficult and effortful process. In Kool and Botvinick's (2014) paradigm, this selection process is ostensibly quite simple due to the discrete nature of reward – a task is either rewarded, or it is not. However, the task selection process becomes more complex after appreciating the fact that the tasks are of unequal difficulty. Participants must (a) determine

how much effort is required to perform the task, (b) determine how much that effort is worth, and (c) subtract that amount from the reward received for performing the task (e.g., the amount of effort required to perform the difficult task might be worth three candies, and the task rewards five candies for accurate performance; therefore, the net-reward of the task is two candies). After this computation has been performed for both tasks, the outcomes of the computations must be stored in memory and compared against each other to make a decision (e.g., the two candy net-reward of the difficult task is weighed against the zero candy net-reward of the easy task). There has been some work investigating the task selection process, for example, how eye movements influence the comparison of choices; Krajbich et al., 2010). But there is little work that can directly speak to the *effort* involved in this process (Rangel et al., 2008). Although research investigating such value-comparison processes is scarce, it is intuitive that this process might become more effortful as the representations become more complex. This provides theoretical motivation for the idea that, as they fatigue, people simply become worse at comparing actions to make a selection. Whether or not this is the case, however, is an open empirical question.

Regardless of whether task selection is an effortful process, it is clear that executing a task does require effort, and investing effort in task execution has consequences for future decisions. The way in which investing effort in execution influences the decision process is unclear, however. Overall, evidence from the behavioral-economic literature reveals that people construe effort as a cost (Smith & Walker, 1993), and that investing effort has consequences for future decisions (Kool & Botvinick, 2014). People require more reward to expend the same amount of effort, but what is the nature of this alteration? Do people simply begin to value effort more, thereby requiring more reward to expend the same amount of effort? Or do people just get worse at comparing task values, and make selections that do not make sense? Getting at the heart

of these questions requires a deeper understanding of the nature of *controlled* effort being exerted in these tasks and, specifically, how controlling effort for one task impacts the control of effort in future tasks. Behavioral economists tend to not consider the influence of effort at such a level in the decision process. To investigate how the control used to perform a task influences the decision process, we turn to the cognitive-control literature.

Attention and Cognitive Control: The Impact of Cognitive Control on Goal-Driven Behavior

Decisions in the real world can often be thought of as choices between maintaining a current course of action and switching to one of many alternative courses of action. Executing one action and switching between actions requires effort, or cognitive control. When switching between many different courses of action, cognitive control is applied flexibly — cognitive flexibility is characterized by the ability to vary behavior adaptively in response to changes in goals or the environment. When maintaining focus on a single course of action and shielding that focus from distraction, cognitive control is applied in a more stable manner — cognitive stability is characterized by the ability to continue pursuing a goal in the face of obstacles or distractions (Shen & Chun, 2011). Both aspects of cognitive control require cognitive effort; however, switching to an alternative course of action is generally more difficult and requires more effort than maintaining performance on the same task (Arrington & Logan, 2004). One prominent method for investigating how cognitive control is recruited to execute and switch between tasks is through the use of the task switching procedure.

Paradigms Investigating the Switch Cost. Task switching is a conventional tool that has been used to investigate the mechanisms of cognitive control (Jersild, 1927). In a task switching paradigm, target objects are presented one-at-a-time on a computer screen, and

participants are able to perform one of two simple tasks on each trial. For example, given the stimulus “4”, a participant could judge whether the digit is odd or even, or judge whether the digit is greater than or less than five. The participant receives a cue indicating which task to perform, and must perform the cued task as quickly and accurately as possible (for a review, see Kiesel et al., 2010). The actual tasks that are performed vary across paradigms, but they are typically simple perceptual judgments and can be performed quite rapidly. Switching to perform the task that was not performed on the previous trial is typically associated with longer RTs than repeating the same task as the previous trial – this is referred to as the switch cost. The switch cost is one of the most robust findings in the task switching literature (Arrington & Logan, 2004; Jersild, 1927), but there is evidence that the cost may be lessened during periods of high cognitive flexibility (Leber, Turk-Browne, & Chun, 2008).

The Task Set

Why is it slower to switch from one task to another than to keep repeating a single task? To draw from a real-world example, consider the tasks involved in cooking dinner. One of these tasks might be preparing a salad, while the other task might be continually stirring pasta in a boiling pot of water so that the pasta does not stick to the pot. The chef needs to switch between the task of stirring pasta and the task of preparing a salad in order to complete the dinner on time. When switching from preparing the salad to stirring the pasta, the chef is probably slower and must take extra care when beginning to stir the pasta to ensure that she does not splash boiling water onto the stove. After several seconds of stirring, the chef can resume her normal, efficient stirring pace. Likewise, when switching from stirring to preparing the salad, the chef is probably initially slower and must remember where she left off and resume the plan involved in making the salad.

Why is the chef slower to stir pasta after having just switched from making salad?

Cognitive-control theories generally postulate that people have mental representations called task sets that correspond to tasks in the real world (Allport, Styles, & Hsieh, 1994; Cohen, Dunbar, & McClelland, 1990; Logan & Gordon, 2001; Logan & Schneider, 2010; Mayr & Keele, 2000; Rogers & Monsell, 1995; Wylie & Allport, 2000). A task set is generally thought of as an internal representation that holds all the information necessary to execute the task that it corresponds to (Rogers & Monsell, 1995). The task set representation must be activated in order for the task to be executed. In the present example, there is a salad-preparation task set (devoted to the salad-preparation task), and there is a pasta-stirring task set (devoted to the pasta-stirring task). When switching from one task to another, one must disengage the task set associated with the no-longer-relevant task, and activate the task set associated with the new task (Allport et al., 1994; Rogers & Monsell, 1995; Wylie & Allport, 2000). When switching from preparing salad to stirring pasta, the chef must stop thinking about the plan for the salad, stop using her hands to assemble ingredients for the salad, and begin thinking about using a spoon to stir the pasta in a fast, but safe way. Inhibiting the salad-preparation task set and activating the pasta-stirring task set takes longer than only keeping the pasta-stirring task set active — hence why switching from one task to another is slower than continually repeating the same task.

There is consensus in the cognitive-control literature that the concept of a task set exists, but there has been much less consensus about what actually constitutes a task set. What information is stored in this internal representation that allows for execution of the task? There is compelling evidence to suggest that the task set, at minimum, consists of the stimulus-response mappings used to execute the task. Some of this evidence even comes from the initial work in task switching (Jersild, 1927), which revealed that when the two tasks at hand are sufficiently

distinct, switching tasks is no more costly than repeating tasks. For example, when one task involves adding three to a digit and another task involves producing the antonym of a word — thus both tasks have distinct stimuli and require distinct responses — switching between tasks takes just as long as repeating one of the tasks. However, when the two tasks have similar stimuli and require similar responses (e.g., one task requires subtracting three from a number and the other requires adding two to a number) switching tasks is significantly slower than repeating tasks.

Let us assume that the tasks in the previous example (preparing a salad and stirring pasta) require overlapping responses, and switching between these tasks indeed comes at a cost. Some have argued that the ease with which a task can be performed depends on the fluency of the stimulus-response mappings (Cohen et al., 1990), and this logic has been extended to the task switching literature to explain the mechanisms of switching between tasks (Gilbert & Shallice, 2002; Yeung & Monsell, 2003). An extreme conception of this perspective would be that the task-set representation *only* consists of the stimulus-response mappings used to execute the task. This would mean that the pasta-stirring task set only includes the processes necessary to perceive the stimuli of the task and translate them into motor responses needed to physically execute the task of stirring pasta (i.e., seeing the spoon, grasping it, and moving it in a circular motion). If the task set is only made up of stimulus-response mappings, it insinuates that the cost of switching from salad preparation to pasta stirring is *only* the result of blocking the stimulus-to-motor pathways associated with preparing a salad and initiating the stimulus-to-motor pathways associated with stirring pasta.

What about everything else that is involved in performing a task? Others have argued that, in addition to stimulus-response mappings, a task set includes top-down goal information

related to the task, and this information can influence the activation of the more automatic stimulus-response pathways (Gilbert & Shallice, 2002; Miller & Cohen, 2001). For example, in the Stroop paradigm, having a strongly maintained goal to perform the ink naming task can enhance performance on that task, even though performance on that task is usually weak because the stimulus-response mappings for the alternative task (i.e., word reading) are more dominant (Gilbert & Shallice, 2002). The notion that the task set includes goal-related factors has prompted more recent theories to postulate that the task-set representation might contain a wide range of information related to the task — including its perceptual and mnemonic characteristics (Mayr & Keele, 2000; Merian, 2010). This leads to rich accounts of the task-set representation, which theorize that the task set includes everything from the goal state with which the task is approached, to the attentional templates used when perceptually attending to task-relevant stimuli, to the stimulus-response mappings of the task (Merian, 2010). These factors can also be thought of as “parameters” in the execution of a task, and some researchers have claimed that a task set can be defined as a stable set of parameters that can computationally explain task performance (Logan & Schneider, 2010). If task performance changes, and the parameters of the model used to describe performance need to be adjusted in order to account for the change in performance, one can claim that the task set has changed.

A majority of cognitive-control researchers have focused on the consequences of switching between task sets while eschewing the central issue of what constitutes a task set (for a review, see Logan & Schneider, 2010). A good deal of theoretical progress has been made by making inferences about how control interacts with the task set, and this progress has shed some light – albeit indirectly – on the content of the task-set representation itself. As previously outlined, initial task switching evidence suggested that, at a minimum, the task-set representation

consists of stimulus-response mappings (Jersild, 1927). There is compelling evidence to suggest that the attentional processes used to encode stimuli relevant to the task (termed attentional templates; Arrington, Altman, & Carr, 2003) are also part of the task-set representation. Switching between two tasks with similar perceptual features is less costly than switching between tasks with disparate features, suggesting that attentional templates can be shared between task sets. For example, the attentional template “form” can easily switch between judging the height and width of a stimulus (Arrington et al., 2003).

More recent evidence has suggested that the stimulus-response mappings in the task-set might in fact be primed. When switching between word naming and ink naming tasks in the Stroop paradigm (Stroop, 1935), participants are slower to name words after previously naming an ink color. Interestingly, responses were slowest when naming words that had been targets in previous trials, rather than when naming words that had not yet been seen in the experiment (Allport & Wylie, 2000). This suggests that, while reconfiguring the word naming task set makes one slower at naming all words, the cost is greatest for naming words that had been named on the previous trials. The authors interpreted this effect as evidence for item-specific priming, wherein the response-pathways for relevant items are strengthened more than irrelevant items within a particular task set (Wylie & Allport, 2000).

The finding that people are slower to name *all* words after ink naming is indeed important (Allport & Wylie, 2000). It suggests that there are task sets that correspond to well-established, real-world tasks. Reading several words is sufficient to activate the processes required to read all words. But the finding that, after ink naming, it is more difficult to name words that were seen recently suggests that the task set is also flexible: All words are activated following word naming, but words that are most relevant to the task at hand receive the most

activation. Therefore, perhaps the task set can be thought of as a stable representation that can flexibly update to accommodate the task at hand. How the task set is updated can depend on the instructions given for the task or the strategy with which the task is approached. It is possible, then, that other information that is relevant to the task at hand might be activated as part of its task set, including higher-order goals. This possibility is difficult to evaluate given existing evidence. Most paradigms investigating cognitive control processes do so in highly constrained environments, where the importance of stimulus-response mappings is at a premium while the impact of goal-related influences is minimized (for a review, see Kiesel et al., 2010). Does the task set representation *only* consist of low-level procedural information essential for executing the task (e.g., stimulus-response mappings and perceptual features), or can the task set generalize to include all information directly relevant to the task at hand? The present research investigates this question by expanding the scope of the task switching paradigm. In an environment where there is relevant information related to the *goal* of executing a task – such as a value associated with choosing the task – does that goal-related information become active in the task set that is used to execute the task?

While these questions are critical to the central hypotheses of the present research, for now we will set them aside and look ahead to see how researchers have used the concept of task set to make theoretical progress in the cognitive-control literature.

Cognitive Control, Task Sets, and the Switch Cost

A rough picture of the switch cost should be emerging at this point – switching to a new task is costly, and this is because task sets need to be reconfigured to perform a new task. But how exactly do task sets get reconfigured in order to perform a new task? The answer to this question lies in how cognitive control interacts with the task-set representation.

Traditional Accounts of the Switch Cost. Two opposing, but not mutually exclusive, theories have been proposed to explain how switching task sets gives rise to the switch cost. Some argue that the switch cost is primarily driven by the use of control to inhibit the previously active task set. This hypothesis claims that a task set's activation persists after the task has been executed; therefore, a crucial step in executing a new task is inhibiting the persisting activation of a previously active task. To draw upon the example from the previous section, the chef needs to completely disengage from preparing the salad before she can stir the pasta. This hypothesis is called the task-set inertia account (TSI; Allport et al., 1994) — the persisting activation of one task set into the performance of another task is called between-task interference (Yeung, 2010). Critically, the TSI account predicts that disengagement from a previously-performed task cannot be fully completed until the stimulus for the new task is presented (Allport et al., 1994). This prediction accounts for the finding that the switch cost is not completely eliminated with ample preparatory time (Rogers & Monsell, 1995). Therefore, some portion of the task set for the previously performed task is still active until the onset of the following trial.

Conversely, some argue that preparing the oncoming task set is responsible for the switch cost; this hypothesis is called the task-set reconfiguration account (TSR; Monsell, 1996). The TSR account postulates that, while preparing for an upcoming task, the switch cost arises as a result of two distinct functions: an endogenous component and an exogenous component. The endogenous component consists of a reconfiguration of task sets to prepare for execution of the task being switched to (e.g., preparing the task set for stirring pasta). More preparation time allows for better reconfiguration and decreased switch costs. The exogenous component is only initiated after the onset of the second task's stimulus, and consists of the inhibition of interference from the previous task (disengaging from the task set used to prepare salad).

Hierarchical Reinforcement Learning. In addition to the two traditional accounts of the switch cost, the hierarchical reinforcement learning model (HRL; Botvinick, Niv, & Barto, 2009) investigates the mechanics of switching tasks along with the goal-driven behavior that drives task selections. This approach is more representative of the hierarchical structure of real world logic: going home after work is composed of packing up supplies, walking to the car, starting the car, etc. The basic concept behind the HRL model is that higher-order goals (e.g., going home after work) can be decomposed into many low-level constituents (e.g., all the tasks that are required in going home after work). These low-level constituents can be broken down even further – packing up supplies is composed of identifying objects needed at home, assembling them into a bag, etc. The HRL model was originally derived from the popular computational reinforcement learning concept in the machine learning domain (Barto & Sutton, 1981) in order to model learning behavior in simple situations. The HRL model was developed as a way to scale up the reinforcement learning algorithm to model learning in more complex environments with many possible world states. One of the central notions in the HRL model is temporal abstraction (Sutton, Precup, & Singh, 1999), which is a way of grouping together many actions that work towards the same goal over a period of time (e.g., hitting specific notes on a piano with the overall goal of playing a song). The representation that contains the temporal abstraction of specific, goal-oriented actions is called an option (Botvinick et al., 2009). Options are thought to be analogous to the concept of task sets, especially in how the representation of the option will persist throughout the execution of specific actions.

Organizing task representation as a hierarchy emphasizes that task performance indeed consists of lower-level procedural components (actions), but it also consists of higher-level goal representations (options). This is in contrast to the task-set theories in the cognitive-control

literature, where a majority of the emphasis is placed on the low-level mechanisms of activating and reconfiguring task sets (Allport & Wylie, 2000; Yeung & Monsell, 2003). Because of the emphasis on the task-set representations and the cognitive processes that act upon them in the cognitive-control literature, it is difficult to generate inferences about the task-selection processes involved in task switching from a goal-driven standpoint. The HRL's goal-driven emphasis serves as an apt platform for the development of theories that can account for the impact of task-set mechanisms on goal-driven behavior (and vice versa). Modeling task performance in a behavioral hierarchy is one way to begin making predictions that are more valid with respect to the decision-making process as a whole.

Task Switching and Rewards. Another way that has proven useful in investigating goal-driven behavior within the realm of task switching is through the use of rewards. When a reward is available for fast and accurate performance on a given trial, participants tend to perform the task faster without sacrificing accuracy (Chiew & Braver, 2014). This is especially notable when a reward is available for performing a task when that task is different from the previous trial, as the usual cost for switching tasks is greatly reduced. Rewarding task performance is thought to affect the flexibility and stability of control during task switching. Over a series of six experiments, Shen and Chun (2011) manipulated reward in a cued task switching procedure to show that rewards can influence the flexibility of performance. They manipulated whether reward was high or low on a given trial, and they independently manipulated whether each trial was a task repetition or a task switch. Results showed that task repetitions were fastest when the amount of reward remained high across trials. However, on trials where the task had switched from the previous trial, performance was fastest when the previous trial was associated with a low reward and the current trial was associated with a high reward. Shen and Chun (2011)

concluded that consistently high reward leads to higher performance stability, whereas increases in reward lead to greater response flexibility. This suggests that not only does the nature of control depend on the current state of goals and reward, but it also depends on how reward is changing relative to previous trials – echoing the phenomenon that people are more sensitive to relative changes in reward rather than objective levels of reward outcome (Kahneman & Tversky, 1979). With respect to the switch cost, there is evidence to suggest that providing rewards reduces the switch cost response time (RT) without a concomitant increase in switch cost for errors (Jimura, Locke, & Braver 2010; Kleinsorge & Rinckenauer, 2012; Locke & Braver, 2008; Shen & Chun, 2011, experiment 2).

The influence of rewards on task switching performance has also been characterized under another dual framework – proactive and reactive control (dual mechanisms of control; Braver, 2012). Proactive control is akin to an early, selection-based process, where the control needed for a task is recruited before the onset of the task and maintained throughout the task. Conversely, reactive control is applied as a late correction, where the appropriate control processes are only recruited on a moment-to-moment basis as needed (Braver, 2012). The default control mode tends to be reactive control, but shifts toward proactive control can be initiated in a variety of ways, such as providing participants with increased time to prepare for task execution (Kleinsorge & Rinckenauer, 2012), or by manipulating whether the upcoming task is expected to be difficult (Burgess & Braver, 2010). Associating rewards with task performance also induces shifts towards proactive control during task performance (Chiew & Braver, 2014; Frober & Dreisbach, 2014; Locke & Braver, 2008), perhaps through increasing motivation for task performance. Increases in motivation can explain why providing rewards reduces the switch cost RT without a concomitant increase in switch cost for errors (Jimura, et al., 2010; Kleinsorge &

Rinkenauer, 2012; Locke & Braver, 2008; Shen & Chun, 2011, experiment 2). This suggests that rewards do not just elicit faster responses, but more efficient responses. Rewarding a response is so powerful that a previously rewarded stimulus can become a distraction once it is no longer relevant. Evidence for this comes from a study using a visual search paradigm (Yantis, Anderson, Wampler, & Laurent, 2012). People are quite good at finding a stimulus in a visual array when there is a consistent reward for that stimulus. But when the target shifts, and they are now looking for a different stimulus, the previously-rewarded stimulus interferes with the visual search. This evidence suggests that reward information can be a feature of a stimulus that automatically captures attention.

In sum, there is evidence to suggest that manipulating goals and motivation (via manipulating rewards) leads to more efficient task performance. However, this research largely focuses on how reward influences cognitive control and not how it influences goal-driven behavior per se. The question emerging from the behavioral-economic literature remains: how does the controlled allocation of effort influence the decision-making process? This question can now be reframed in more specificity with respect to cognitive-control processes: how do the control mechanisms involved in executing and switching between task sets influence the process of selecting between tasks?

Voluntary Task Switching. The cued task switching paradigm offers an ideal platform for investigating how various factors (including reward) influence the mechanisms that give rise to the switch cost. However, because task choices are constrained by the task cue, the impact of reward can only be considered with respect to its influence on task performance, not task selection. This makes it difficult to generate inferences about how factors such as reward can influence the relationship between control and decision-making processes (e.g., task selection).

The *voluntary* task switching paradigm (VTS; Arrington & Logan, 2004) takes a crucial step towards addressing this concern. VTS is identical to cued task switching with one subtle and crucial difference: there is no longer a cue. By removing the cue, participants are free to choose which task to perform on each trial. Participants are instructed to perform the tasks equally often and in a random order throughout a block of trials.

Evidence from this paradigm reveals the same basic finding as cued task switching — that participants will, on average, respond slower when switching rather than when repeating tasks (Arrington & Logan, 2004). However, this paradigm is more effective in investigating choice behavior by offering participants the freedom to choose between tasks on each trial. Consequently, a key benefit of the VTS paradigm is the ability to model task selection as an outcome variable. When instructed to select between tasks equally often and in a random order, participants tend to repeat tasks more frequently than they switch tasks (repetition bias; Arrington & Logan, 2005). The repetition bias is a good example of the influence of task execution on task selection. Because it is easier to keep the task set for the previously-performed task active than it is to switch task sets, people tend to keep performing a task that was just performed. The stimulus itself can bias task selections as well – people are significantly more likely to repeat tasks when the stimulus from the previous trial repeats (Mayr & Bell, 2006). Together, these results suggest that, although an internal goal is maintained throughout task switching, between-task interference is robust in its ability to interrupt internal goals of task selection. Additionally, from a paradigmatic standpoint, this evidence lends support to the notion that task selection data can serve as a unique window into the mechanisms underlying cognitive control in task switching.

In sum, the primary benefit of the VTS paradigm is the removal of the task cue – allowing participants to choose between tasks throughout the experiment (according to the overarching instructions of the experiment). This allows the mechanisms underlying cognitive control to be investigated with respect to task selections – an empirical advantage that is absent in the cued task switching paradigm. However, as it stands, the VTS paradigm is not well suited to investigate how cognitive control mechanisms influence *goal-driven* decision making *per se*. The instruction to perform tasks randomly is somewhat of an artificial abstraction, and is not representative of task selection in the real world; people do not select real world tasks randomly, but rather they might select them in a way to most efficiently achieve higher-level goals. On the other hand, evidence from cued task switching suggests that associating a task with a reward leads to enhanced task performance. However, this evidence cannot speak directly to reward's influence on task-selection processes because decisions in this context are constrained by the task cue.

Where does this leave us? The behavioral-economic literature focuses on the psychological factors that influence decision making – most notably, for present purposes, how effort can be construed as a cost against reward when selecting tasks to perform. The cognitive-control literature demonstrates how expending controlled effort to perform a task can impact performance of the next task. In contexts where task choices are unconstrained, this literature also highlights how expending controlled effort can influence the *selection* of the next task. However, this influence has only been examined when the task-selection criterion is abstract (e.g., perform tasks equally often and in a random order). In order to investigate how cognitive-control mechanisms influence the type of selection processes outlined in the behavioral-economic literature, the criterion for task selection should be more concrete. Replacing the

abstract instructions in VTS with concrete task values may be one way to investigate this intersection. Implementing task values could also make the goal-driven aspect of the experiment more salient. Participants might be more likely to internalize the goal of pursuing reward than they are to maintain and adhere to (seemingly arbitrary) experimenter instructions.

The Present Research

What are the mechanisms by which expending effort on task performance influences the task-selection process? The present research investigates this question by more deeply investigating the nature of the task-set representation. We have thus far painted a picture of the task set as a stable representation that can be flexibly updated according to the relevant features of the task at hand. This is in line with findings in the task-switching literature, such as that the word-reading task set is used for reading all words, but those words that have been read recently are most active (Allport & Wylie, 2000). We further assert that – if goal-related information is relevant for task performance – it will be active in the task set. This assertion extends the logic of the flexibility of the task set. If the task set can adjust to highly activate the most relevant stimulus-response mappings, perhaps it can also adjust to include relevant goal-related information. This assertion is also in line with theoretical accounts that postulate goal states as part of the task set representation (Botvinick et al., 2009; Meiran, 2010). If the value or reward for a task is important for the goal of performing that task, it should be represented in the task set. But the notion that task value can become integrated into the task set is also supported by other trends observed in the literature. There is evidence that the attentional template used to discriminate the stimuli of the task is included in the task set (Arrington et al., 2003); it is easier to switch between perceptually compatible rather than incompatible tasks. There is also evidence that reward can become integrated into the attentional template used to seek out stimuli (Yantis

et al., 2012); a previously rewarded feature that is no longer relevant to the task at hand can automatically capture attention and serve as a distractor. Therefore, if reward can be integrated into the attentional template, and the attentional template can be integrated into the task set, it is possible that task value can be indirectly integrated into the task set via the attentional template.

The lack of consideration of goal-related information in the task set amongst cognitive-control researchers is due, in part, to such a high emphasis on the procedural properties used to execute tasks. Consequently, the cued task switching paradigms that are traditionally used to investigate the task tightly constrain the environment such that the emphasis is almost solely on stimulus-response mapping. In contexts where other aspects of the task are important for performance (e.g., value), do those aspects become represented in the task set as well? In other words, it is unclear whether stimulus-response mappings are the only defining feature of the task-set across all contexts, or whether the task-set representation can adapt to include goal-related information (particularly value) that is most relevant to performing the task at hand.

Previous research investigating the impact of rewards in task switching has tended to manipulate reward independently from task (Chiew & Braver, 2014). While this manipulation is useful for examining the impact of rewards on cognitive control, it is not informative of whether or not reward is represented in the task set because these two constructs are independent. Initial work in our laboratory took a first step towards merging task and reward representations by first tying rewards to transitions. The paradigm we implemented was meant to emulate an exploit / explore foraging environment (Cohen, McClure, & Yu, 2007) – where participants receive diminishing rewards for exploiting task repetitions, and full reward for a task switch. We found that participants were sensitive to both the rate and probability of reward loss while making task selections, suggesting that participants are able to consider both the explicit reward for

performing the task as well as the implicit effort cost associated with performing the task — a value / effort tradeoff that is consistent with ideas of labor supply theory (Smith & Walker, 1993). The present research modifies this basic design further by systematically assigning values to tasks instead of transitions. This design will further reveal how participants balance value and effort while making task selections, but it will also investigate whether the task value becomes active in the task-set representation when value and task are systematically related to one another.

The TSI account posits that a task is executed by activating its task set, while inhibiting activation from competing task-sets. To switch tasks, the activation of the no-longer-relevant task set must be inhibited, and the previous inhibition that was applied to the now-relevant task must be overcome. The interference from previous tasks in disrupting performance of the present task is generally referred to as between-task interference (Yeung, 2010). There is compelling support for the TSI account in both cued and voluntary task switching paradigms, with the underlying idea being that the stimulus-response mappings must be inhibited and reconfigured for successful task performance (Yeung, 2010). However, if the task set represents all information most important for performing the task, this information should persist after task execution as well. Therefore, we propose a *value-integration hypothesis*, which posits that, when task value is a critical feature for task performance, it will be represented in the task-set representation. This means that, after performing a task at trial N-1, that task's stimulus-response mappings *and* value information will both be highly active (relative to the non-performed task) at the onset of trial N. When choosing between tasks at trial N, because task value is represented in the task set and the task-set representation persists after task execution, participants should be more sensitive to changes in the value of the task performed at trial N-1 than they are to changes

in the value of the non-performed task. Therefore, participants should be more likely to switch tasks in situations where the previously-performed task's value decreases (regardless of how the non-previously-performed task's value changes), and they should be more likely to repeat the same task when the value for that task has remained the same or has increased (again, regardless of how the non-previously-performed task's value changes).

If this is not the case, and the task-set representation contains *only* the stimulus-response mappings needed to execute the task, these specific value sensitivity biases should not emerge. We assume that if task value is not represented in the task set, it is held in a separate representation that does not persist after task execution. If value and stimulus-response mappings are held in separate representations, it is possible that they may interact in a different fashion, but we do not expect to observe the pattern of value sensitivity described above. Rather, we might expect that participants are equally sensitive to changes in value across the two tasks.

Our laboratory has investigated the relationship between task values and task sets by conducting a pilot study where values were systematically assigned to tasks. However, participants rarely fixated task values during task selection (as observed through eye tracking). Experiment 1 adjusted for this by presenting the task values more centrally near the target stimulus to increase value accessibility. The motivation for increasing accessibility of task values was to bias participants to more readily incorporate these values into task selections, thereby creating an environment where the impact of task values on task selections is most likely to be observed. The primary motivation for Experiment 1 was to investigate the core prediction of the value-integration hypothesis – a value-sensitivity bias in favor of the active task set.

While Experiment 1 made task values more accessible, Experiment 2 made task values less accessible. This experiment was similar to our pilot, except the task values were not visible

until directly fixated. The primary purpose in enacting this change was to ensure that participants are accessing task values and, crucially, to know *when* fixations are taking place. This allows for a deeper investigation of the impact of gaze on the relationship between changes in task value and task selection.

Lastly, Experiment 3a and 3b utilized a task difficulty manipulation to investigate how value sensitivity changes when tasks are mismatched on difficulty. Experiment 3a was a direct replication of Yeung (2010, Experiment 1a) – investigating how the switch cost is influenced by task difficulty in VTS. Experiment 3b was aimed at integrating the paradigms of Experiment 1 and Experiment 3a in order to take a more precise look at how task values interact with task difficulty to impact task selection. These subtle, but crucial changes allowed for the impact of task value on task selections to be interpreted with respect to established theories in the cognitive-control literature.

Experiment 1

Experiment 1 directly investigated the relationship between task-specific rewards and task selections using reward-based VTS (rVTS), where instructions are replaced with reward in a VTS context. In short, rVTS systematically assigns values to two tasks. The value for a task will probabilistically decrease after that task has been performed, and it will probabilistically increase when the other task is performed. Participants are informed to accumulate 500 points as fast as possible in each block. This design makes the more time costly course of action (switching tasks) generally associated with higher reward. Throughout all the experiments, the active task is referred to as the *current* task, or the task that was performed on the previous trial. Conversely, the inactive task is referred to as the *other* task, or the task that was not performed on the previous trial. Our central prediction is expressed in Figure 1. The specific contrast between

switch rates in the Current Change and Other Change cells of the design should speak to the relationship between task value and task set (see Figure 1). Specifically, on the value-integration hypothesis, participants should be more sensitive to changes in the current task's value when making task selections – consequently, we expect to observe higher switch rates in the Current Change cell than in the Other Change cell. However, if task value is held in a separate representation from task set, participants should not exhibit a value-sensitivity bias to the current task's value – any other pattern of results would be evidence against the idea that task value can be incorporated into the task set. The present paradigm was specifically designed to address the following question: how does representation of reward interact with cognitive-control mechanisms to predict task selections?

This design is also well suited to examine the role of effort in value-based decision making. The task selection process changes as more effort is used to execute tasks (Kool & Botvinick, 2014), but it is unclear whether people begin to value effort more or whether they just get worse at selecting tasks. The present experiment investigates these possibilities by examining how the representation of effort influences the task selection process. On each trial in rVTS, participants theoretically need to determine the value of each task. This is done by weighing the reward associated with the task against the effort needed to perform the task, meaning that some representation of how much effort will be required to perform the task needs to be constructed.

It is unclear whether constructing a representation of the amount of effort required for a task is something that happens automatically or requires deliberation. Recall that we consider the value of a task to be its reward minus the effort needed to execute it. Consider what the task selection process looks like if constructing a representation of effort needed for the task requires deliberation. When little effort is needed to execute a task, the value of that task is not much

different from the reward associated with that task. Because the representation of effort, in this case, does not have a great impact on the task value, the task value can be computed quickly. However, this process changes when great effort is needed to execute a task. The representation of effort now plays a large role in computing the value of a task – the reward associated with the task needs to be subtracted from the large amount of effort when determining the task value. If constructing and manipulating a representation of effort for a task requires deliberation, it should take longer to determine the value of more effortful tasks. Therefore, there will be a decrease in efficiency of task selection as the tasks become more effortful to execute. However, if the representation of effort for a task can be constructed and manipulated automatically, computing the value of an effortful task should not require more deliberation than computing the value of a less effortful task. In this case, selecting between effortful tasks should be just as efficient as selecting between non-effortful tasks.

The efficiency of task selection in rVTS was measured using block completion times. Participants were instructed to accrue 500 points as quickly as possible, meaning that on each trial participants must quickly compute which task will give them the most amount of points in the least amount of time. Lower block completion times should therefore reflect more efficient task selections. We were then able to analyze whether this efficiency varied as a function of the effort needed to execute tasks. As in any task switching paradigm, the switch cost is a good index of how much more effort is required when switching tasks versus when repeating tasks (Arrington & Logan, 2004). But the size of this cost also varies between individuals (Arrington & Yates, 2009). Some individuals need to invest a great amount of effort when switching tasks, while some individuals do not need to invest as much effort. We had participants perform an independent, cued task-switching procedure to gain a measure of switching ability for each

participant. If high switch cost individuals exhibit longer block times than lower switch cost individuals, it would lend evidence to the idea that constructing and manipulating the representation of effort for a task is a deliberative process. Conversely, if there is no difference in efficiency between high and low switch cost individuals, it might suggest that the representation of effort for a task can be constructed and manipulated automatically.

In addition to analyzing individual differences in switching ability, it is possible that individual differences in reward sensitivity might predict performance efficiency. Because the beneficial impact of rewards on task performance is assumed to be mediated through shifts in motivation (Shen & Chun, 2011), we predict that the relationship between rewards and performance will be moderated by reward sensitivity. Specifically, individuals who are lower in trait reward sensitivity will not be sufficiently motivated by the reward structure and therefore exhibit less efficient performance than those high in trait reward sensitivity.

Method

Participants

Participants were recruited from Lehigh University and participated in the experiment as an optional course requirement. Participants were required to have normal or corrected-to-normal vision and color vision. Data were initially collected from 73 participants; however, 9 participants were dropped due to error rates greater than 15%, and 3 participants were dropped due to switch costs more extreme than ± 2 standard deviations from the overall mean during the cued switching portion of the experiment. This left 61 participants for final analysis.

Tasks

Cued Task Switching. In order to gain a baseline measure of switch cost for each participant, participants completed blocks of cued task switching. Participants were presented with bivalent stimuli that were either red or blue and either a circle or triangle. All stimuli were 1.98 cm by 1.98 cm and presented at center fixation. Therefore, participants could either perform a shape judgment or color judgment on each stimulus presentation. Responses were mapped to keys “F”, “D”, “J”, and “K”, and specific response mappings were counterbalanced across participants. However, mappings were constrained such that both response keys for a task were mapped to either the left or right hand. On each trial, a cue appeared that read either “Shape” or “Color”. Participants were instructed to perform the task that aligned with the cue as quickly and accurately as possible.

To allow for consideration of preparation effects, we manipulated preparation time in all experiments. This was done in the present experiment by beginning each trial with a blank screen that was presented for either 100 ms or 1,000 ms. The cue word then appeared on the screen for either 1,000 ms or 100 ms. The cue word was presented in the upper portion of the screen. After this period, the cue remained on the screen while the stimulus appeared at center fixation and remained on the screen until the participant gave a response. After a response was received the trial sequence restarted. The response-stimulus interval (RSI) was constant at 1,100 ms.

Reward-based Voluntary Task Switching (rVTS). The same stimuli, tasks, and response mappings as the cued task switching portion of the experiment were implemented in rVTS. However, the cues were eliminated, and the tasks were each assigned specific values. Each task value was displayed in 18-point Courier New font, and appeared either 1.69 cm (64 pixels) to the left or the right of center fixation and corresponded to the tasks mapped to the left and right hands, respectively. The task values were digits with range 0 through 10, and the values

represented the number of points participants would receive for accurate performance of the task that the value was associated with (e.g., accurate performance of the task mapped to the left hand results in a gain of the point value displayed on the left side of the stimulus, and vice versa).

Procedure

Participants first completed an informed consent form upon arriving to the laboratory. The experimenter then introduced the participant to the two basic tasks (color and shape) and participants completed 16 trials practicing the tasks separately. Participants were then introduced to cued task switching, and performed 16 trials of practice for cued task switching. Once the experimenter was confident the participant understood the task, the participant then began 3 blocks of 20 trials of cued task switching. The participant was instructed to work through these blocks and to alert the experimenter when this portion of the experiment had concluded.

After performing the cued task switching blocks, participants were introduced to rVTS. Participants performed a total of 12 blocks of rVTS. At the beginning of each block the task values were matched at five points each. Each trial began with the presentation of the point values associated with each task. We manipulated preparation interval in rVTS for the same reasons as in the cued procedure – to elicit larger switch costs and deter participants from entering into a stable responding rhythm. Additionally, due to the exploratory nature of these studies, it would be beneficial to know whether the effects we observe vary as a function of preparation time. If task value is incorporated into the task set representation, and the task set either decays or is inhibited over time, we might expect greater sensitivity to the current task's value at shorter rather than longer preparation intervals. To manipulate the preparation interval, the point values were presented on the screen for either 200 ms or 1,100 ms before the onset of the target, and this interval varied between blocks. The target was then presented at center

fixation. The target remained on the screen until a response was given. The task that was attempted was coded according to which hand was used for the response; tasks were systematically mapped to a specific hand throughout the experiment, and these mappings were counterbalanced across participants. Following accurate task performance, the point value associated with the performed task would be added to participants' total points. The stimulus would then disappear, and the trial sequence repeated (see Figure 2).

On the ensuing trial, there was a 50% chance that the value for the previously performed task would decrease by a point (or remain constant). Meanwhile, there was an independent 50% chance that the value for the non-previously performed task would increase by a point (or remain constant). The total *difference* between task values was defined as the current task's value subtracted from the other task's value – meaning that a positive difference indicates that the other task's value is greater than the current task's value. The font color of the task values changed color to indicate the relative transition on each trial (green: increase by one point, red: decrease by one point, black: remain constant). Point values for each task were bounded between 0 and 10. Each block continued until 500 points were reached. Once participants reached 500 points, the time it took to complete the block was displayed on the screen. Participants were instructed to try and lower their block completion time as the experiment progressed.

The experimenter thoroughly explained how points are awarded and how points transition from trial to trial based on task selections. Critically, once the experimenter was confident that participants fully understood the reward structure, he/she instructed participants to “try to work out a strategy of choosing tasks that works best for you.” Participants then completed 16 trials of practice of rewarded voluntary task switching. Barring any questions, the experimenter then prepared the participant for performing 12 blocks of rewarded task switching,

each block to 500 points. After completion of these blocks, participants completed a computerized version of the Behavioral Inhibition and Behavioral Activation Scales (BIS/BAS; Carver & White, 1994); this was a 24-item questionnaire with questions that measure the approach and avoidance motivational systems that are theorized to underlie behavior.

Results

Trial-by-trial Shifts in Reward

Data Cleaning. Error trials, the trials following error trials, and the first trials of each block were excluded from the analysis, resulting in 74% of cases retained for analysis. These trimming criteria were adopted for analysis of both the cued task switching procedure and the rVTS procedure. For the analysis of RTs in rVTS, RTs shorter than 200 ms and longer than 3000 ms were trimmed from the analysis.

Reward and Task Selection. To assess the impact of task-specific rewards on the choice to switch or repeat tasks, a 2 (current: constant vs. change) X 2 (other: constant vs. change) within-participants ANOVA was conducted on the proportion of task switches (descriptive statistics are displayed in Table 1). There was a main effect of current, such that switch rates were significantly higher in the current change condition ($M = .42$, $SE = .03$) than in the current constant condition, ($M = .32$, $SE = .02$), $F(1, 60) = 47.07$, $p < .001$, $\eta_p^2 = .44$. Additionally, there was a main effect of other, such that switch rates were significantly higher in the other change condition ($M = .45$, $SE = .03$) than in the other constant condition, ($M = .29$, $SE = .02$), $F(1, 60) = 66.71$, $p < .001$, $\eta_p^2 = .53$. Critically, there was a significant interaction of current and other, $F(1, 60) = 23.82$, $p < .001$, $\eta_p^2 = .28$. To follow up the interaction, the mean difference across levels of other is compared across the two levels of current. The cell means reveal a larger difference in

switch proportions across levels of the other task's value transition while the current task remains constant (.20), than across levels of the other task's value transition while the current task has decreased by a point from the previous trial (.12). Crucially, in looking at the a priori contrast between the Current Change and the Other Change cells of the design (Figure 1), mean switch proportions when the other task's value has increased while the current task's value has remained constant ($M = .43$, $SE = .03$) are significantly higher than switch proportions when the other task's value has remained constant while the current task's value has decreased, ($M = .38$, $SE = .03$, $F(1, 60) = 15.60$, $p < .001$, $\eta_p^2 = .21$; see Figure 3).

Task Performance. To analyze task performance in rVTS, a 2 (RSI: long vs. short) X 2 (transition: repetition vs. switch) within-participants ANOVA was conducted on mean RTs. This analysis revealed a main effect of transition ($F(1, 61) = 125.98$, $p < .001$, $\eta_p^2 = .67$), with faster RTs for task repetitions ($M = 694$ ms, $SE = 41$) than for task switches ($M = 1034$ ms, $SE = 36$ ms). There was also a main effect of RSI ($F(1, 61) = 66.65$, $p < .001$, $\eta_p^2 = .52$), with faster RTs for longer ($M = 746$ ms, $SE = 34$ ms) rather than shorter preparation times ($M = 810$ ms, $SE = 37$ ms). There was also a significant interaction of transition and RSI ($F(1, 61) = 124.22$, $p < .001$, $\eta_p^2 = .67$) suggesting that the switch cost was smaller at longer RSIs (238 ms) rather than shorter RSIs (508 ms). However, follow-up tests revealed that the switch cost was significant at both short ($M_{\text{Repetition}} = 691$ ms, $SE_{\text{Repetition}} = 33$ ms; $M_{\text{Switch}} = 1198$ ms, $SE_{\text{Switch}} = 39$ ms; $F(1, 61) = 982.15$, $p < .001$, $\eta_p^2 = .94$) and long RSIs ($M_{\text{Repetition}} = 679$ ms, $SE_{\text{Repetition}} = 40$ ms; $M_{\text{Switch}} = 917$ ms, $SE_{\text{Switch}} = 39$; $F(1, 61) = 221.78$, $p < .001$, $\eta_p^2 = .78$). RTs were not analyzed across the reward structure because participants were more likely to switch tasks when reward changed rather than remained constant, and slowed RTs are associated with task switches.

Reward Differential and Task Selection

Analyzing trial-by-trial changes in current and other is only informative as to relative transitions in value of the tasks. This analysis says nothing about whether or not the task selection process changes when one task has a much higher value than the other – for example, the task selection process may change when one task is worth eight points and the other is worth three versus when both tasks are worth five points. Therefore, it may be useful to include the total difference between task values as a predictor of task selections. Including trial-by-trial changes in current and other as well as the total difference in a model predicting task selections will reveal whether the basic findings from the ANOVA analysis hold across all levels of the difference between task values. Additionally, because participants were informed as to the nature of the reward structure and told to develop their own strategy of responding, there were large between-participant differences in the approach to the experiment. For this reason, random effects were included in order to control for between-participant variability. Thus a generalized linear mixed model was adopted for this analysis in order to both control for random effects and model a combination of discrete and continuous variables in predicting task selections.

Design. In order to analyze the impact of current, other, and the total difference in value between the task on task selections, a generalized linear mixed model was used through the use of the lme4 package (Bates, Maechler, Bolker, & Walker, 2015) in R (R Development Core Team, 2016). Specifically, transition served as the binary outcome (0 = repeat, 1 = switch). Just as in the ANOVA analysis, current (0 = constant, 1 = change), and other (0 = constant, 1 = change) were included as predictors, where constant indicated that value had not changed from the previous trial and change for current indicated a decrease by one point from the previous trial whereas change for other indicated an increase by one point from the previous trial. The total difference between task values was also included in the analysis, and was computed as the other

task's value minus the current task's value. Thus the range of the difference variable was -10 to 10, where larger positive values reflect a larger difference in favor of the other task, and larger negative values indicate a larger difference in favor of the current task. The final model included all main effects and interactions of current, other, and difference predicting the outcome of transition.

Data Preprocessing. Plotting a histogram of the difference variable (see Figure 4) revealed that, for the most part, participants responded in ways to keep the difference between task values close to zero. This means there were few observations where one task was substantially higher in point value than the other. In order to avoid making predictions over levels of the difference variable where there were few observations, and in order to retain the most data possible, observations greater than or equal to positive four were grouped together, and observations less than or equal to negative four were grouped together. Although the difference variable was treated as a continuous predictor in the model, it was in essence a discrete variable with nine levels: less than or equal to negative four, a range from negative three to positive three, and greater than or equal to positive four.

Qualitatively looking at the entire distribution of the difference variable revealed a surprisingly high proportion of observations at difference equal to positive ten. This is odd because having many observations at level ten on the difference variable suggests repeating a task at value zero while the other task is at value ten. This behavior is unlikely to be a strategic approach to the task, and might suggest a failure to comprehend task instructions or a lapse in motivation in a particular block. Perhaps the best way to look for cases where participants are not performing the task correctly is to examine outliers on the block time measure. A participant who is not engaged in the experiment (either in a single block, or throughout the entire duration of the

experiment) is likely to have long block completion times. Blocks that were slower than two standard deviations from the mean of all block times were removed from the analysis. Trimming based on this criterion removed 4% of the data. This trimming procedure did not completely exclude any participants from the analysis. Further, it was important to ensure that each participant was still contributing a sufficient number of observations to the analysis (e.g., a participant could have had 11 out of 12 blocks trimmed). Observations were summed across participants. This revealed that no participant's observation count was less than two standard deviations from the mean, suggesting that each participant was contributing a sufficient number of observations. The model with random effects that best fit the data was used for the analysis. The β estimates are converted to odds ratios for ease of interpretability and reported along with their significance values. These odds ratios are converted to probabilities in figures, again for ease of interpretability.

Task Value Difference and Task Selection. There was a main effect of current, suggesting that when the current task's value has decreased by a point from the previous trial, the odds of switching tasks increase by a factor of 1.75 ($p < .001$). Moreover, an increase in the value of the other task from the previous trial increases the odds of switching tasks by a factor of 2.69 ($p < .001$). The interaction between current and other ($\beta = 0.60, p < .001$) indicates that, when the current task's value has decreased by a point and with the difference between the task values held constant at zero, a one-point increase in the other-task value is associated with an increase of the odds ratio of switching by a factor of 0.60. These basic effects of current and other converge with the findings from the ANOVA analysis to suggest that, overall, people are more likely to switch tasks when the current task's value decreases and when the other task's

value increases. But they tend to be more sensitive to changes in the other task's value than the current task's value when making task selections.

Recall that the difference variable is coded as the value of the current task subtracted from the value of the other task. Therefore, positive values for this variable represent a difference in favor of the other task, while negative values represent a difference in favor of the current task. A one unit increase in the difference between task values increases the odds of switching by a factor of 2.29 ($p < .001$). There was a significant interaction of current and difference ($\beta = 1.05, p < .001$), suggesting that – when the current task's value has decreased from the previous trial – each unit increase in the difference is associated with a 1.05 increase in the slope of the difference variable. In other words, participants became more sensitive to changes in the current task's value as the difference in value between the tasks increased in favor of the other task (see Figure 5). To follow-up this interaction, the simple slope of current was tested at both 3 points above and below zero on the difference variable. As expected, the simple effect of current at high levels of the difference was significant ($\beta = 1.56, p < .001$) suggesting that, when the other task's value is greater than that of the current task, the odds of switching increase by a factor of 1.56 when the current task's value has decreased in value from the previous trial (opposed to remaining constant). Critically, at low levels of the difference, the simple effect of current is much weaker ($\beta = 1.24, p = .04$), although still significant. This suggests that when the current task is of greater value than that of the other task, trial-by-trial changes in the current task's value are not as significant in predicting the odds of switching. All other interactions with the difference in the model failed to reach significance ($ps > .05$; see Table 3).

Switch Ability and Reward Sensitivity. In order to determine whether individual differences in switching ability and reward sensitivity predicted performance efficiency, two

separate bivariate analyses were conducted. Switching ability was determined for each participant as the mean switch cost during the cued task switching procedure (see Table 2); reward sensitivity was determined from the reward sensitivity subscale of the BIS/BAS. Bivariate correlations between these measures and performance efficiency were analyzed. Performance efficiency was defined as mean block completion times for each participant – with lower values indicating more efficient performance. However, these analyses suggested that neither mean switch cost ($r = 0.08$) nor reward sensitivity ($r = 0.08$) was associated with mean block completion time.

The impact of switching ability and reward sensitivity was also analyzed for task selection. Switching ability and reward sensitivity were included as between-participant predictors in two separate generalized linear mixed models predicting task transition. Neither the main effect of reward sensitivity nor any of its interactions were significant factors in the model (all $ps > .05$). There was a significant three-way interaction between switch cost, current, and the difference ($\beta = 1.00, p = .04$). This interaction was followed up by examining the simple effect of current across people with high and low switch costs (plus and minus one standard deviation from the mean) at both high and low levels of the difference (see Figure 6). At low levels of the difference, the simple effect of current was not significant for low or high switch cost individuals (all $ps > .05$). At high levels of the difference, the simple effect of current is significant for high switch cost individuals ($\beta = 1.79, p = .01$), but not low switch individuals ($p = .47$). This means that – at high levels of the difference – the current task decreasing value (rather than remaining constant) leads to a larger increase in the odds of switching for high switch cost individuals but not low switch cost individuals. Whereas – at low levels of the difference – changes in the

current task's value do not lead to significant increases in the odds of switching, regardless of individual differences in switch cost.

Experiment 1 Discussion

Experiment 1 was an initial investigation into the relationship between representation of task value and the task set. This experiment investigated the impact of task rewards on task selections, and the impact of individual differences in both switching ability and reward sensitivity on performance efficiency. Two main research questions were addressed, namely: (a) how does representation of reward interact with cognitive control mechanisms to predict task selections, and (b) do individual differences in switching ability or reward sensitivity predict performance efficiency?

Rewards and Task Selection. Changes in task value had a clear influence upon task selection. Specifically, participants exhibit expected task choices by switching tasks at a significantly higher rate when both task values have changed from the previous trial, as opposed to when both task values have remained constant from the previous trial. This suggests that value comparison processes are present in an rVTS environment, and can partially account for task selections. However, it is interesting to note that switch rates when both task values have remained constant from the previous trial are non-zero. Logically, if a participant has evaluated the task values and has selected a task to perform, given that the values do not change on the ensuing trial, it would make most sense perform the task again – thus minimizing switch costs. While switching tasks in this scenario is difficult to explain, it is not an unprecedented finding. Spontaneously switching tasks in a context where it is not ostensibly advantageous is a robust effect (Kessler, Shencar, & Meiran, 2009). Some researchers hypothesize that spontaneous switching may be due to disruption from internal processes, such as mind wandering (Smallwood

& Schooler, 2006), or disengagement from task demands (Weismann, Roberts, Visscher, & Woldorff, 2006). However, there are intuitive reasons for spontaneous switching in the present experiment's context. Perhaps the simplest explanation is that people might simply become bored, and choose to switch tasks as a way to stimulate their attention. It could also be part of an exploratory behavior, where participants will resample the difficulty of switching as to re-compute the value of switching tasks. Whatever the reason for spontaneous switching, we have no reason to believe it would not be balanced across conditions, thus it should not confound our a priori analysis.

Bias in Sensitivity to Other Task. The value-integration hypothesis predicts that participants would exhibit greater sensitivity to changes in the current task's value than the other task's value when making task selections. This would have manifested as a bias to be more sensitive to the value of the active task set – supporting the notion that task value may be a feature of the task set. However, this experiment revealed the opposite pattern of results. Participants exhibited a value-sensitivity bias in favor of the other task, with higher switch rates when the other task's value has increased from the previous trial (while the current task's value remains constant) than when the current task's value decreases from the previous trial (while the other task's value remains constant). Further, looking at this interaction broken down across the total difference between task values reveals that this trend is consistent across all levels of the difference. Participants were more sensitive to changes in the other task's value regardless of whether the value of the other task was three points greater or three points less than that of the current task. This is not only evidence against the notion that task value might be a feature of the task set, but these data suggested that there might be a process at work that biases higher sensitivity *towards* the non-active task-set's value. However, this result could be trivially

explained by a stimulus-driven confound in the experiment – the font color of task value presentation was systematically tied to its transition (black was constant, green was increase, red was decrease). To investigate this possibility, a replication of Experiment 1 was conducted with task values displayed in constant black font color. This replication revealed the same significant contrast – higher switch rates when the other task’s value increased from the previous trial (while the current task’s value remained constant) than when the current task’s value decreased from the previous trial (while the other task’s value remained constant; see Appendix A). Therefore, at present, this pattern of results fails to support the value-integration hypothesis.

It is difficult to explain why there would be greater sensitivity to changes in the other task’s value than to changes in the current task’s value. It might be tempting to explain these results under the loss aversion phenomenon – where people tend to be more averse to losses than they are drawn to chasing gains (Kahneman & Tversky, 1978). This might explain why people avoid attending to the current task’s value, because it will only ever display loss or neutral information, whereas the other task’s value will only ever display gain or neutral information. However, there are several problems with such an interpretation. First, loss aversion only applies to the prospect of *losing* resources. In this paradigm, a decrease to the current task’s value only reflects a decrease in the amount of reward that could be received, not a decrease in the amount of points the participant has already accrued per se. Second, loss aversion could have been just as easily applied to explain the opposite pattern of results. If people are more averse to losses, they could be more likely to monitor information that is directly relevant to losses as a way to avoid losses as much as possible. This would predict a bias to attend to changes in the current task’s value and greater switch rates in response to decreases in the current task’s value as opposed to increases in the other task’s value. Therefore, we hesitate to explain the pattern of results using

ideas from prospect theory and loss aversion, especially since there are no true losses to participants' point total at any time during the experiment.

The present pattern of results could potentially be explained by bottom-up, attention-capture processes. Because the point values never disappear from the screen, a changing point value from one trial to the next may result in a “flashing” change phenomenon, and be more visually salient than a value that has remained constant from the previous trial. This is consistent with work showing that attention is captured by sudden stimulus onset (Jonides & Yantis, 1988). Once attention is captured by a value, it is possible that merely fixating the value will facilitate preference towards the task associated with the value, regardless of whether that value has increased or decreased from the previous trial. This would be in-line with the mere exposure effect (Kunst-Wilson & Zajonc, 1979), which claims that fixating an item is sufficient to facilitate preference for that item. The mere exposure effect has been shown to influence choices in controlled, dual-choice contexts, where participants make preference judgments about food options (Krajbich et al., 2010). Consider the Current Change and Other Change cells of the rVTS design, where only one value changes while the other remains constant. It is possible that attention is captured by the changing value. Once attention is drawn to the changing value, attending to the value associated to the task could facilitate preference for the task, regardless of how the value has transitioned from the previous trial. For the other task, this would only facilitate the preference for selecting this task when the value has increased. For the current task, this would attenuate the aversion to selecting this task when the value has decreased. This would in turn explain why participants appear to be more likely to switch when only the other task's value has increased rather than when only the current task's value has decreased. Because the role of attentional capture in preference formation in the present paradigm is speculative, we

more closely examine the influence of eye movements on the relationship between value change and task selections in Experiment 2.

Point Difference and Task Selection. The total value difference between the tasks had a strong influence on task selection. As the other task's value increased over the current task's value, participants were more likely to switch tasks. Further, the impact of trial-by-trial changes in current task's value was stronger as the difference between the task values increased in favor of the other task's value. This was evidenced by a significant interaction between difference and current, such that decreases in current task's value had a significantly higher association with switching tasks when the value difference between the tasks was higher in favor of the other task than for the current task. This suggests that, while the current task's value is greater than the other task's value, participants are less sensitive to trial-by-trial changes in the reward structure. This is consistent with the notion that performance of a task associated with consistently high rewards is associated with more cognitively stable responses, which results in an increased likelihood to repeat the highly rewarded task (Shen & Chun, 2011). If there is greater value for the current task, there should be no reason to switch, and all information that is not related to repeating tasks should be ignored. However, once the other task's value becomes greater than the current task's value, this could lead towards a more cognitively flexible state of responding (Shen & Chun, 2011), where the incentive of increased value for switching tasks must be weighed against the effort cost of switching tasks.

Switching Ability, Reward Sensitivity, and Performance Efficiency. Overall, individual differences in both switching ability and reward sensitivity were mostly unrelated to performance efficiency. For reward sensitivity, it could be the case that the present paradigm was too highly constrained to allow for individual differences in reward sensitivity to impact

efficiency. The BAS reward-responsiveness scale was developed to measure the degree to which individuals approach outcomes associated with reward. These contexts are often complex and unconstrained, and it is possible that a general inclination to pursue reward does not significantly influence performance in a context where the only goal is to pursue reward as fast as possible.

The fact that switching ability was unrelated to performance efficiency lends support to the idea that task selection may be more of an automatic process. High switch cost individuals are not worse than low switch cost individuals at rVTS – high switch cost individuals' task selections must just as reasonable (or just as unreasonable) as those of low switch cost individuals.² This suggests that the added effort required for high switch cost individuals to switch tasks does not add an extra burden to their ability to compare and select between tasks.

There was evidence that individual switching ability might influence what information is attended to while making task selections. The interaction between changes in current task's value and the overall difference is moderated by switch cost, such that the impact of current does not change across levels of the difference for low switch cost individuals. However, for high switch cost individuals, the impact of current increases as the difference between task values increases in favor of the other task. It is possible that, if high switch cost individuals place a higher value on switching tasks, they would both wait for the other task to have a much higher value than the current task and – when it does – be more sensitive to trial-by-trial changes in task value when making the decision to switch. However, this does not explain why they would only exhibit

² There is no objective measure of performance efficiency in rVTS. Instead, block completion times serve as a more normative and subjective measure of performance efficiency. Thus we cannot, in principle, claim that high and low switch cost individuals are equally “good” or “bad” at rVTS, but just that they not different in terms of efficiency.

increased sensitivity to trial-by-trial changes in the *current task's value* (sensitivity to changes in other task's value was non-significantly different across high and low switch cost individuals).

Alternatively, this pattern of results could still support the idea that high switch cost individuals are simply be worse at comparing task values to make selections. If value comparison is an effortful process, this might lead high switch cost individuals to have less cognitive resources available for comparing task values. A lack of resources available to task selection might lead to a stronger reliance on one source of information to drive task selections (changes in the current task's value) rather than comparing task values to make task selections. This could explain why low switch cost individuals have a high probability of switching in response to increases in total value difference between the tasks, and high switch cost individuals have a higher probability of switching in response to changes in the current task's value (see Figure 6). Although this interpretation is attenuated by the finding that low switch cost individuals did not perform the task more efficiently than high switch cost individuals. Because the individual difference effects in this experiment were slight, we hesitate to draw strong conclusions about the automaticity or effortful nature of the task selection process based on this evidence. Future work should strive to disentangle these two possibilities, perhaps by finding a more precise measure of what would constitute “optimal” behavior in the rVTS context.

In sum, evidence from Experiment 1 stands in contrast to the value-integration hypothesis, suggesting that task value might not be represented in the task-set representation that is used to execute the task. This evidence further suggests that individual differences in switching ability and reward sensitivity are largely unrelated to performance efficiency (although switching ability may predict task selections in some contexts). In Experiment 1, because the values were displayed immediately next to the target stimulus, it is assumed that participants

incorporated task values into task selection choices on each trial. Therefore, it would be pertinent to gain a measure of when participants are fixating task values, and how fixating task values impacts task selections. Experiment 2 attempted to capture this information by measuring eye movements during task performance.

Experiment 2

Many cognitive processes occur before a decision is reached, and tracking eye movements is one way to capture these processes (Day, 2010; Fiedler & Glockner, 2012, Hristova & Grinberg, 2008). Tracking eye movements during binary decision tasks has revealed that people tend to fixate more to alternatives that have greater importance to the decision, termed the utility effect (Fiedler & Glockner, 2012; Glockner & Herbold, 2011; Glockner, Fiedler, Hochman, Ayal, & Hilbig, 2012, Hristova & Grinberg, 2008; Kim, Seligman, & Kable, 2012). Kim et al. (2012) had participants either bid on an object or choose one of two gambles. Overall, participants are more sensitive to probability changes when choosing between two gambles, but more sensitive to value when bidding. Eye tracking data reaffirmed this bias by showing that – when values and probabilities are displayed on a screen – people will fixate more on probabilities when selecting a gamble, and more on value while making a bid (Kim et al., 2012). Fixation patterns and tendencies can be used to identify decision strategies that were never before observable with strictly RT data (Day, 2010; Krajbich et al., 2010), such as revealing how fixations can construct preferences during value-based decision making (Krajbich et al., 2010).

However, an alternate perspective on the relationship between fixations and preference contends that fixations actually play a causal role in preference formation. In a binary decision setting, this perspective assumes that the first fixation will be randomly selected between the two

options. The option that receives more fixations will accumulate more evidence and consequently have a higher likelihood of being chosen (Krajbich et al., 2010). The notion that fixating an object causes an increase in preference is termed the gaze cascade theory (Shimojo, Simion, Shimojo, & Scheier, 2003); this theory's claim that fixations play a causal role in preference formation is highly controversial, and recent evidence suggests that gaze fixation may not actively construct preferences, but is rather a passive means of acquiring information (Bird, Lauwereyns, & Crawford, 2012; Nittono & Wada, 2009).

The validity of gaze cascade theory has been investigated by exogenously manipulating attention through the use of gaze contingent displays (Armell & Rangel, 2008; Glaholt & Reingold, 2011; Lim, O'Doherty, & Rangel, 2011; Richardson, Spivey, & Hoover, 2008). Overall, these studies find some, but not full, support for the gaze cascade theory — interrupting participants' fixations is associated with a choice bias towards the last fixated object (Richardson et al., 2008). Such results advocate more for the impact of mere exposure on preference formation (Kunst-Wilson & Zajonc, 1979), and, at the very least, impugn the causal role of fixations in preference formation. This interpretation is in line with other studies, which suggest that choices are a function of time spent computing the decision, along with previous experience with the decision alternatives (Armell & Rangel, 2008). These findings serve to further attenuate the gaze cascade theory and allude to a softer interpretation of the role of eye movements in preference driven decision making. Although these conflicting results fail to disambiguate the role of gaze in decision making, gaze contingent displays are a hopeful future avenue for parsing apart the different contributions of gaze and preexisting preferences on preference-based decision making.

The present experiment investigates the role of fixations in the relationship between task values and task selections. To what extent does task selection on the previous trial influence fixation to value on the current trial, and how does fixation to task value impact task selection? These questions are addressed in the present experiment by implementing a gaze contingent display that does not reveal task values unless fixated. This provides a measure of which task values are being accessed on each trial. Further, this measure allows for a more in-depth investigation of the decision processes involved in task selection by analyzing the interaction between value changes and fixations on task selection.

We predict that when participants make fixations to both task values in a given trial, task selections will be largely in-line with our predictions for Experiment 1, outlined in Figure 1. There will be the highest switch rates when both tasks have changed value, lowest switch rates when both task values remain constant, and moderate switch rates when one task value changes while the other remains constant. However, when only one task value is fixated during a trial, we predict a sensitivity bias will emerge, such that participants will be more sensitive to changes in the fixated value than to changes in the non-fixated value. If neither task value is fixated during the trial, task selections should be independent of value transitions from the previous trial, because the numbers to indicate the task values will be physically unavailable on the screen.

This design may speak to the causal nature of fixations in decision making. Although the paradigm is different from that used in preference-based decision research, if fixation patterns predict task selections independently of the reward structure, it might suggest that task selections are being driven by a process other than value comparison. For example, if a fixation to the other task's value is predictive of a task switch even if that task has not increased in value from the previous trial, it could suggest either that something implicit to the fixation itself is driving a

subjective increase in value for performing that task (in-line with gaze-cascade theory), or that an endogenous motivation to perform a task (independent of its value) drives fixation to that task value and ultimately drives selection of the task.

The additional information collected from eye tracking allowed for a more in-depth exploration of the decision process in the present experiment. Specifically, this study analyzed the impact of changes in value on fixation patterns, and the interaction of value changes and fixation patterns on task selections. It is possible that the impact of changes in task values on task selection could be mediated through fixation patterns. Therefore, these analyses are generally organized into a mediation model (see Figure 7), where task value changes predict fixation patterns and task selections, and fixation patterns also predict task selections.

Method

Participants

Fourteen participants were recruited from Lehigh University to participate in this study. All participants had normal or corrected to normal vision, and color vision. Participants participated in the research for optional course credit. No participants had error rates higher than 15%, and so all participants were retained for analysis.

Apparatus

Eye tracking data were collected using a 24-inch T60XL eye tracker (Tobii Technology, Stockholm, Sweden). The eye tracker has a frequency of 60 Hz and accuracy of approximately 0.5 visual degrees. Participants were seated 60 cm away from the device with their heads rested in a chin rest to increase stability of the eye tracking. Areas of interest were defined at central fixation 5.93 cm left of central fixation for left task feedback, and 5.93 cm to the right of central

fixation for right task feedback. Areas of interest were 2.65 cm in width and 2.65 cm in height. Task reward feedback was programmed to display once a fixation is recorded within the area of interest for that respective feedback.

Task

Rewarded Voluntary Task Switching. The task used in this experiment was similar to the task used in Experiment 1 with several slight changes. Most notably, the value information was placed on the far left and right edges of the screen. The information was also gaze contingent, and did not appear unless fixated.

Procedure

Each trial began with a blank slide that was presented for 500 ms. After this period, a fixation cross appeared in the center of the screen, along with two placeholders on both the left and right sides of the screen. The placeholders were comprised of four periods presented above, below, to the left, and to the right of a space on the screen. Areas of interest (AOI) were defined around the placeholders. The placeholders and fixation cross remained on the screen for 500 ms. After this period had elapsed, there was a 1000 ms value search period. During this period, participants could fixate the left target, the right target, both targets, or neither target. Once gaze entered the AOI surrounding the placeholder, the corresponding task value was displayed within the placeholder and remained on the screen throughout the remainder of the trial. After the 1000 ms value search period had elapsed, and the judgment stimulus appeared for 7000 ms or until a response was received. If the participant made an incorrect response, the word “error” was presented in red font directly above the stimulus for 500 ms. After the error feedback was presented, the trial sequence restarted. If the participant made a correct response, the trial

sequence repeated without the 500 ms presentation of the error feedback. Each block terminated when the participant reached 200 points, at which point the time it took to complete the block was presented on the screen (see Figure 8). The nature of the reward structure was identical to that of Experiment 1, such that the value of the performed task would either remain constant or decrease by a point, while the value of the non-performed task would either increase by a point or remain constant. However, the font color of the task values no longer changed color as a function of trial-by-trial changes in task value, but remained black throughout the experiment.

Participants performed 16 trial practice blocks of both tasks separately, and a 16 trial block of rewarded VTS (with no gaze contingency; task values were visible at all times). Following practice blocks, participants were introduced to the nature of the gaze contingency. The experimenter then calibrated the eye tracker, and left the room while the participant completed the experiment. The experimental session consisted of 12 blocks, each terminating when the participant reached 200 points. The session was divided into two halves of six blocks each. Participants were instructed to rest as needed between blocks. Following the first six blocks, the experimenter reentered the room and informed the participant that he/she could rest as needed until the start of the second half. Once the participant indicated he/she was prepared to continue, the experimenter recalibrated the eye tracker and left the room while the participant completed the second half of the experiment.

Results

Trial-by-trial Shifts in Reward

Data Cleaning. The same data trimming procedures from Experiment 1, including trimming at ± 3 on the difference variable, were conducted in the present experiment on the

behavioral data, leaving 65% of original cases for final analysis. Eye tracking data were only analyzed during the value search period. A fixation to task value was only coded as a “true” fixation if there were at least six consecutive fixations to task values already recorded. Fixation to task value was coded as ending once a fixation was no longer recorded within the AOI. Therefore, the first six fixations in a sequence of fixations to task value were not included in the measure of time spent dwelling on task values.

Reward and Task Selection. To assess the impact of changing task values on task selections, a 2 (current: constant vs. change) X 2 (other: constant vs. change) within-participants ANOVA was conducted on task transitions (see Figure 9). Switch rates were significantly higher when the current task’s value decreased by a point from the previous trial ($M = .52, SE = .05$) than when the current task’s value remained constant from the previous trial, ($M = .33, SE = .04$), $F(1, 13) = 31.97, p < .001, \eta_p^2 = .71$. Additionally, switch rates were significantly higher when the other task’s value increased by a point from the previous trial ($M = .52, SE = .05$) as opposed to when the other task’s value remained constant from the previous trial, ($M = .32, SE = .03$), $F(1, 13) = 32.77, p < .001, \eta_p^2 = .72$. Interestingly, there was no interaction between current and other, $F(1, 13) = 1.09, p = .32, \eta_p^2 = .08$.

Task Performance. To investigate task performance, RTs were analyzed across transition (and not RSI, because it remained constant). This analysis revealed that task switches were significantly slower ($M = 962$ ms, $SE = 91$ ms) than task repetitions ($M = 795$ ms, $SE = 75$ ms; $t(13) = 4.99, p < .01$). Again, RTs were not analyzed across the reward structure because participants were more likely to switch tasks when reward changed rather than remained constant, and slowed RTs are associated with task switches.

Total Fixations

To take an initial look at fixation patterns throughout a trial, the frequency with which participants fixated task values at all during a trial was investigated. Specifically, during the value search period of any given trial, a participant could adopt one of the following four fixation strategies: fixate only the current task's value, fixate only the other task's value, fixate both task values, or fixate neither task value. Gaining a sense of fixation tendencies is critical in guiding the more nuanced analyses of eye tracking measures, namely first fixations and dwell times.

Because the number of trials varied across participants, the frequency with which participants employed one of the four fixation strategies across trials was calculated as a percentage of each participants' total trials (see Table 4). Overall, participants fixated both task values during a trial in 61.73% ($SD = 34.49\%$) of trials, only fixated current task's value in 12.21% ($SD = 12.96\%$) of trials, only fixated other task's value in 10.40% ($SD = 7.55\%$) of trials, and fixated neither task value in 16.34% ($SD = 22.17\%$) of trials. The variability around these estimates is quite high, and it was primarily driven by two participants who fixated both task values on less than 1% of trials. Removing these two participants changed the overall percent of fixations to both task values in total trials to 71.19% ($SD = 25.92\%$). Because there were so few observations for the remaining three fixation strategies, and the observations varied widely between participants, all ensuing eye tracking analyses were conducted on trials where fixations to both task values were recorded. In addition, the two participants who rarely fixated both task values in a trial were dropped, leaving 12 participants for analysis.

Dropping these trials ensures a more homogeneous pattern of fixations across participants when analyzing more nuanced aspects of the fixation data. First, the impact of both the first fixated value in a trial and the proportion of dwell time between the two task values on task

selections was analyzed. A mediation analysis was then conducted examining whether changes in task value influenced task selections through fixations to task values.

First Fixations

As an initial investigation of first fixation patterns across trials, the impact of previous task on first fixation was analyzed. Is there a higher likelihood of fixating the current task first, other task first, or are participants first fixations unrelated to the task that was previously performed? A one-sample t-test was conducted to investigate whether the average proportion of fixating the current task's value first was significantly different from 0.5. This analysis revealed that participants do not significantly fixate task values as a function of the task that was previously performed (current: $M = .52$, $SE = .02$; $t(11) = 1.19$, $p = .26$).

To investigate the role of first fixations in task selections on the current trial, the interaction of first fixation and value changes on the current trial was analyzed. Specifically, on trials where both task values were fixated, first fixations on each trial were coded as either a first fixation to the current task or to the other task. This measure was then integrated with the measures from previous design, yielding a 2 (first fixation: current vs. other) X 2 (current: constant vs. change) X 2 (other: constant vs. change) within-participants ANOVA on the proportion of task switches.

There was a significant main effects of current ($F(1, 11) = 96.35$, $p < .001$, $\eta_p^2 = .90$), indicating higher switch proportions when the current task has decreased from the previous trial ($M = .59$, $SE = .04$) than when the current task had remained constant from the previous trial ($M = .34$, $SE = .04$). There was also a main effect of other ($F(1, 11) = 75.46$, $p < .001$, $\eta_p^2 = .87$), indicating higher switch proportions when the other task increased value from the previous trial

($M = .59$, $SE = .04$) than when the other task remained constant from the previous trial ($M = .34$, $SE = .04$). However, there was no main effect of first fixation ($F(1, 11) = 2.03$, $p = .18$, $\eta_p^2 = .16$), nor were there any significant interactions between first fixation and the other factors in the model, all $F_s < 1$. Analyzing the mean switching proportion in a separate analysis across only levels of first fixation (not including trial-by-trial value transitions of current and other) revealed that participants were significantly more likely to switch after first fixating the other task's value ($M = .49$, $SE = .04$) than after first fixating the current task's value, ($M = .38$, $SE = .05$), $t(11) = 2.77$, $p = .02$. However, because this factor failed to reach significance in the omnibus model, this result must be interpreted conservatively.

Dwell Proportion

Calculating Dwell Proportion. To conduct a more nuanced investigation of the role of eye movements on the relationship between reward and task selection, a dwell proportion measure was calculated for each trial. This measure is formally expressed as follows [3]:

$$\frac{Dwell\ Current}{(Dwell\ Current + Dwell\ Other)} \quad (3)$$

where dwell current equals the sum of observations fixating the current task's value fixations throughout the trial, and dwell other equals of the sum of observations fixating the other task's value throughout the trial. Therefore, this measure is bounded at zero and one, and values closer to one indicate a higher proportion of the trial spent fixating the current task's value (relative to the other task's value), while values closer to zero indicate a higher proportion of the trial spent fixating the other task's value (relative to the current task's value).

A Process Model of Task Selections. The dwell proportion measure was incorporated into a process model of task selections. The impact of trial-by-trial changes in reward (on the

present trial) on dwell proportion was investigated. An interaction between current and other may reveal a selective bias in sensitivity towards value changes in either the current or other task. Finally, generalized linear mixed models were run to analyze the impact of trial-by-trial changes in current and other, dwell proportion, and stimulus repetitions on the likelihood of switching or repeating tasks. Like in Experiment 1, all generalized linear mixed models were run using the glmer function in the lme4 package (Bates et al., 2015) in R (R Development Core Team, 2016).

Present Trial Value Changes and Dwell Proportion. To examine whether task value changes from the present trial predict dwell proportion on the present trial, a 2 (current: constant vs. change) X 2 (other: constant vs. change) within-participants ANOVA was conducted on the dwell proportion. This analysis revealed a marginal main effect of current ($F(1, 11) = 4.75, p = .05, \eta_p^2 = .30$), indicating a greater proportion of dwelling the current task's value after the current task had remained constant from the previous trial ($M = .52, SE = .007$), than when the current task had decreased by a point from the previous trial ($M = .50, SE = .004$). There was a significant main effect of other ($F(1, 11) = 6.70, p = .03, \eta_p^2 = .38$), indicating a greater proportion of dwelling the current task's value when the other task's value had remained constant from the previous trial ($M = .51, SE = .007$), than when the other task's value had increased from the previous trial ($M = .50, SE = .003$). The two-way interaction was not significant, $F < 1$.

Dwell Proportion and Reward. To investigate the impact of dwell proportion and reward on task selections, a generalized linear mixed model was conducted with transition (0 = repeat, 1 = switch) regressed on: current (0 = constant, 1 = change), other (0 = constant, 1 = change), and dwell proportion (continuous from 0 = only fixate other task's value, to 1 = only fixate current

task's value), along with all the two- and the three-way interaction(s) of these variables³. All random effects were estimated by participant, and all fixed effects were initially included as random effects – however, the model failed to converge with all random effects specified. Random effects were removed until convergence criteria were met. A model with only the intercept, and main effects and interaction of current and other was the first to reach convergence. A LRT test revealed that this model fit the data significantly better than the next most simple model (removing the interaction of current and other; $X^2(1) = 225.5, p < .001$). As in Experiment 1, observations were tightly clustered around zero on the total point value difference between the tasks. Restricting the difference variable between -3 and 3 resulted in a significantly lower AIC for the model fitting the restricted data ($AIC = 4910.06$) than for the unrestricted data, $AIC = 5370.48$. Models used for all the following analyses are fit to the restricted difference dataset. All β estimates were converted to odds ratios to aid interpretation (see Table 5).

Consistent with the results of the ANOVA, there were significant main effects of both current ($\beta = 3.32, p < .001$) and other ($\beta = 3.46, p < .001$) suggesting that changes in value from the previous trial (decreases for current, increases for other) are associated with an increase in the odds of switching tasks. Unlike the ANOVA, this analysis controls for dwell proportion, so the main effects of current and other can be interpreted as significant predictors of task selection when subjects fixated task values equally throughout a trial. Again, there was no reliable interaction of current and other while fixating both tasks equally throughout a trial, $\beta = 0.72, p$

³ Stimulus repetitions heavily bias participants to repeat tasks (Mayr & Bell, 2006). To control for this, the generalized linear mixed model with dwell proportion and reward predicting task selection was run with stimulus repetition as a fixed effect, along with all interactions including stimulus repetition. This analysis revealed that stimulus repetition was not a significant factor in the model, nor did it interact with any of the variables in the model to predict task selection. Therefore, stimulus repetition was dropped from the model, but stimulus repetition trials were not dropped from the analysis.

=.14. The main effect of dwell proportion was significant ($\beta = 0.24, p < .001$), suggesting that each unit increase in dwell proportion (looking more at the current task's value) was associated with a 0.24 factor decrease in the odds of switching tasks when both the current task and other task have not changed value from the previous trial. To further investigate whether the main effect of dwell proportion was robust to changes in the reward environment, the analysis was re-run with effect-coded versions of current and other. This allowed for the main effect of dwell proportion on task selections to be interpreted as averaged over changes in current and other task's values, rather than only for when the current and other task's values remain constant from the previous trial. This analysis revealed that averaging over the levels of current and other does not moderate the significant impact of dwell proportion on task selections, suggesting that a one unit increase in dwell proportion (fixating the current task's value more during a trial) is associated with a 0.38 factor reduction in the odds of switching tasks when averaging across the levels of current and other ($p < .001$).⁴

Finally, there was a marginally significant interaction between the current task's value and the dwell proportion ($\beta = 1.81, p = .07$), suggesting that the difference between the odds of switching after the current task's value has decreased rather than remained constant from the previous trial increase on trials where the current task's value is fixated to a greater proportion (see Figure 10). In other words, participants are more likely to switch in response to a decrease in the current task's value after fixating that value at a greater proportion throughout the trial. To further investigate this interaction, dwell proportion was centered at plus and minus one standard

⁴ Additionally, including the main effect of the difference between task values into the model did not moderate the significance of dwell proportion either — a one unit increase in dwell proportion is associated with a 0.39 factor reduction in the odds of switching tasks both averaging across the levels of current and other and holding the value differential constant at zero ($p < .001$).

deviation from the mean and the analysis was re-run for both the high and low dwell proportion terms. As expected, at high levels of dwell proportion (trials where the current task's value was fixated at a higher proportion than the other task's value), the main effect of current was significant ($\beta = 3.13, p < .001$). However, the main effect of current was also significant at low levels of dwell proportion ($\beta = 2.63, p < .001$). Therefore, dwell proportion does not fully moderate the impact of current task's value transition on task selection, but the odds of switching (when the current task's value has decreased) increase by a larger factor at higher rather than lower levels of dwell proportion.

Mediation Analysis. Because changes in current task's value marginally interacted with the dwell proportion to predict task selections, and dwell proportion did not fully moderate the impact of current task's value transition, it is possible that the impact of current task's value transition on task selections was mediated through dwell proportion (see Figure 7). The regression coefficient between current task's value and dwell proportion was statistically significant ($\beta = -0.02, p = .02$), suggesting that a decrease in the value of the current task is associated with increased fixation proportion to the value of the other task.

To determine estimates for the remaining two pathways in the mediation model, a logistic regression was conducted with current task's value transition and dwell proportion predicting transition. A decrease in point value in the current task from the previous trial is associated with a 3.08 factor increase in the odds of switching ($p < .001$) while fixating both values about equally throughout the trial (dwell proportion mean centered at 0.51). Additionally, each unit increase in dwell proportion is associated with a 0.61 factor reduction in the odds of switching tasks ($p = .01$) while the current task's value has remained constant from the previous trial. The indirect effect of current task's value transition on task selection through dwell proportion was 0.002; the

direct effect of current task's value transition on task selection was 0.27. The significance of direct and indirect effects were tested through bootstrapping procedures. Indirect and direct effects were computed for 5,000 bootstrapped samples, and 95% confidence intervals were computed by determining the indirect and direct effects at both the 2.5th and 97.5th percentiles. The 95% confidence interval for the indirect effect ranged from 0.00005 to 0.004 ($p = .04$); the interval for the direct effect ranged from 0.24 to 0.30 ($p < .001$). Therefore, the mediated effect is small, but significant. Moreover, the relationship between changes in the current task's value and task selection is not fully mediated by dwell proportion, as the direct effect is significant.

Experiment 2 Discussion

Experiment 2 investigated the relationship between shifting task values, fixations to task values, and task selections. One of the primary questions motivating this experiment was, to what extent are participants utilizing task values in driving task selections? Evidently, the predominant strategy was to fixate both task values on each trial – so much so that there were not enough data to analyze responses under any other context. Reducing, or eliminating, the value search period could pressure participants such that fixating both task values on each trial would result in too great of a time cost. Consequently, participants would have to adopt a shortened fixation strategy. This shortened fixation strategy may resemble the bias from Experiment 1 to be more sensitive to changes in value of the other task than to changes in value of the current task. Tracking eye movements in this context might be revealing of the nature of this bias. Specifically, when fixing values under time pressure, are participants more likely to only fixate the other task's value? If participants are still fixating both task values under time pressure, why is there a bias to be more sensitive to changes in value of the other task? Future research should

aim to track eye movements in a higher time-pressured environment to explicitly address these questions.

Secondly, how does visually accessing task values impact task selection? We originally posited that task selections would be biased by the values that are accessed throughout the trial: responses would be in-line with the reward environment following fixations to both task values, whereas selectively accessing only the value of the current or other task would result in a heightened sensitivity bias to changes in the current or other task's values, respectively.

Interestingly, participants only tended to fixate both task values on each trial. This allowed for more nuanced eye tracking measures to be implemented to test for finer sensitivity differences in fixating current and other task's values as an alternate way of testing our original prediction.

Moreover, these measures were also used to investigate whether fixating task values is associated with task selections independently of changes in the reward structure.

Rewards, fixations, and task selections. Before addressing the nature of the relationship between task values and fixations in predicting task selections, it is interesting to note that there was no interaction between current and other in predicting task selections, as was observed in Experiment 1. The lack of an interaction could be due to the present experiment introducing a “value search period”, where participants have 1000 ms to compare task values before the onset of the target stimulus. This extended value comparison period could have served to eliminate sensitivity biases between value changes in the current and other task. In the same vein, this could be the explanation as to why first fixation did not predict, or interact with any factors, to predict task selections. First fixations may not be as influential of a factor in selections with the

reduced time pressure of 1000 ms for strictly comparing task values.⁵ Conversely, first fixations may play a larger role in a more time-pressured environment, where time used for fixating task values directly subtracts from RT to the target stimulus. Because there was increased time for task value fixations in the present experiment, this could explain why dwell proportion to task values was most predictive of task selections.

Overall, trial-by-trial changes in the task values did not interact with dwell proportion to predict task selection. Instead, the value changes and dwell proportion independently predicted task selections. This is a puzzling result, and one that runs counter to our prediction; we expected that dwell proportion's impact on task selections would depend on the changes in the task values. However, there was a marginal interaction between changes in the current task's value and dwell proportion, and this interaction was in-line with our prediction – participants were more likely to switch tasks when the current task's value had decreased from the previous trial, and this tendency was magnified on trials where participants fixated the current task's value at a higher proportion. In further investigating this relationship, it appears as though the relationship between changes in the current task's value and task selections is partially mediated through dwell proportion. In other words, a decrease in the value of the current task was associated with higher dwell proportions to the other task's value, which was associated with a higher likelihood

⁵ It is also possible that first fixation was not as powerful a measure in the present experiment due to the 500 ms “wait” period that preceded the 1000 ms value search period, where fixations revealed task values. It is possible that, during this period, participants could have made several fixations before the “first” fixation was recorded. However, because the values were not displayed until a fixation was recorded during the value search period, the first fixation measure did indicate which value was accessed first, but perhaps not necessarily which task value was attempted to be accessed first.

of switching tasks. This suggests that changes in the reward environment influence attention, which informs the task selection process.

Again, it is possible that the strength of these associations could be attenuated by the presence of the value search period, where participants are able to fixate task values in the absence of the target stimulus. When there is an extended, pressure-reduced period to accumulate task-value information, the relationship between task value transitions and fixations could influence task selections at a more abstract level. Theoretically, when there is ample time to acquire and compare values, participants could be accessing task values, storing these values as internal representations, and comparing these representations to compute a task selection. The notion that increased preparation time is associated with increased optimality of task selections is supported by evidence from VTS. Participants more closely adhere to the instructions of performing tasks randomly when there is added preparation time, exhibiting decreased repetition biases (Arrington & Logan, 2004, 2005; Liefoghe, Demanet, & Vandierendonck, 2010, Yeung, 2010). Additionally, increased preparation time is associated with shifts towards proactive control (Braver, 2012). This might explain why, in the present experiment, task selections were largely rational with respect to task values, but – in Experiment 1, with less preparation time – a value sensitivity bias emerged when relying more on reactive control. Because tracking fixations would not directly index the comparison of task value representations, it could explain why the observed interaction between task values and dwell proportion was marginal at best. A more time-pressured environment could potentially lead to shifts towards reactive control and strain the evidence accumulation process. Value search in this context may prioritize efficiency over completeness, and only access information that is considered most relevant to the task selection, rather than accessing all value information, comparing the task value representations, and

computing a rational task selection. In this context, the task values that are accessed should be highly predictive of task selections.

Dwell Proportion and Task Selection. This experiment revealed a significant main effect of dwell proportion, such that the proportion of time spent dwelling on a task value positively predicted selection of the fixated task, controlling for trial-by-trial transitions in task value and for the overall difference between task values. This pattern of results might be most readily explained by the mere exposure effect (Kunst-Wilson & Zajonc, 1979). Fixating a value associated with a task might facilitate preference to perform that task. However, it is puzzling why dwelling on task value would facilitate preference for a task independently of how the value changed from the previous trial.

Recall the explanation for the increased sensitivity to changes in the value of the other task in Experiment 1: Attention is attracted by the visual saliency of value change from one trial to the next; once attention is directed to a value, preference is facilitated for the task associated with the value through mere exposure to the value, leading increases in the other task's value to become more attractive and decreases in current task's value to become less aversive. Why would mere exposure to values interact with value change in Experiment 1 but be (mostly) independent of value change in Experiment 2? One critical difference between these experiments is that in Experiment 1 values remained present on the screen throughout each trial while in Experiment 2 values were not displayed on the screen during a trial until they were fixated. Therefore, in Experiment 2, value changing from one trial to the next would not result in a visually salient, capture phenomenon, as it did in Experiment 1. Instead, value from the previous trial must have been stored in memory and actively compared to the value in the current trial in order to assess how the value has changed. In contexts where participants do not remember

values from the previous trial, it is reasonable that impact of mere exposure to values would be independent from value changes in predicting task selections. However, value changes did exert a strong influence on task selections, so it is reasonable to think that participants were able to compare changes in value across trials. It is therefore surprising that – although there was a marginal interaction between changes in current task’s value and dwell proportion – there was not a stronger interaction between value changes and dwell time in predicting task selections overall.

Finally, because fixations are rather equally distributed between both task values following execution of the previous task, it lends further support to the notion that representation of task value is distinct from the task set used to execute the task. If value is represented in the task set, and the representation of value thus persists into the ensuing trial, we would expect attention to be directed towards the value associated with the active task set. This bias could manifest as a tendency to both fixate the current task’s value first and to dwell on the value for a greater proportion of time than the other task’s value. Because this is not the case, it suggests that the active task set has minimal influence on the value search and comparison process – providing further evidence that task value is not represented in the task set.

Experiment 3a

One of the more counterintuitive findings in the cognitive control literature is the impact of task difficulty on both task choices and switch costs. Until now, the present discussion of task switching has largely focused on contexts where tasks are functionally matched on many characteristics (e.g., difficulty, previous exposure, value, etc.). However, this is not always the case, and some of the most substantial progress in distinguishing between competing theories of the switch cost has come from manipulating the characteristics of the tasks themselves and

observing what influence these characteristics have on the switch cost. Insights from these manipulations may also shed light on the relationship between task value and task set. A clear example of this is when one task is more difficult to execute than the other task. Yeung (2010) presented shapes in one of three, horizontally-aligned cells on a computer screen. Participants could respond on each trial by either judging the shape of the target stimulus or its location in one of the three cells. The location task was compatibly mapped (i.e., the right cell mapped to the right-most finger, the left cell mapped to the left-most finger, etc.). Because of this mapping, the location task was much easier to perform than the shape task. Participants exhibited unequal switch costs depending on the task that was being switched to. Intuitively, one might think that the longer switch cost would occur when switching to the more difficult task (i.e., it is hard to switch to a hard task). However, this was not the case – participants incurred a greater cost when switching from the difficult (shape) task to the easy (location) task, than they did when switching from the easy task to the difficult task (Yeung, 2010). What does this pattern of results reveal about the nature of the switch cost?

The explanation for these findings involves considering how automatic the tasks are. An easy task is automatic and therefore easy to execute. A hard task is effortful and therefore more difficult to execute. Yeung (2010) argues that, while an automatic task requires little control, an effortful task requires a high degree of control to both (a) activate its task set and (b) block the activation of the more automatic task set. Because the TSI account assumes that task set activation persists after task execution, and that the persisting activation needs to be inhibited before execution of a new task can begin (Allport et al., 1994), the way one thinks about the switch cost should be flipped: The switch cost does not depend on what task participants are switching *towards*, but rather what task participants are switching *away from*. When switching

away from the hard task, Yeung argues that a high degree of control is necessary to both (a) disengage from the persisting activation of the effortful task set, and (b) overcome the previous inhibition of the automatic task set. This process is slower than when switching from an automatic task to an effortful task. Because the task is automatic, it can be performed with relatively little control; therefore, disengaging from an automatic task set is not as costly of a process. In describing the relationship between task automaticity and the switch cost, Yeung (2010) uses the terms “strong” to refer to an automatic task set and “weak” to refer to an effortful task set. A strong task is one that people have a strong natural ability to perform effectively (i.e., automatic), and a weak task is conversely one that people have a weak natural ability to perform effectively (i.e., effortful). To make my discussion of these constructs more aligned with Yeung’s (2010), I will adopt his terminology moving forward.

The idea that the switch cost is larger when switching *away* from a difficult task is called the paradoxical asymmetrical switch cost (PASC; Yeung, 2010). In this context, the word “paradoxical” simply refers to the fact that asymmetry of the switch cost is counter-intuitive. The PASC has not only been observed in contexts where two tasks vary in difficulty (Yeung, 2010), but also in contexts where tasks vary in how much they are practiced (Yeung & Monsell, 2003b), and in familiarity (Yeung & Monsell, 2003a). Despite the growing body of evidence in support of the TSI account (due to observing the PASC), endorsement of this account in the literature is not ubiquitous.

Umemoto and Holroyd (2014) propose an alternate account to explain the switch cost asymmetry, suggesting that an HRL account (Botvinick et al., 2009) is a more adequate and valid explanation for the switch cost in task switching. They propose that the reinforcement for a given task is instantiated at the higher “option” level of the hierarchy. In order to maintain fast and

accurate performance on the reinforced task, rigorous top-down control must be applied to this task throughout performance. For example, when one task is associated with a higher reward than the other, people will apply more control to performing the task associated with the higher reward. The critical difference between the HRL account and the TSI account is the way in which task strength is defined. Umemoto and Holroyd (2014) do not define task strength by the automaticity of the response mappings of the task (as the TSI account does; Yeung, 2010), but rather they define task strength according to the amount of control applied to the task: the more control that is applied to the task, the stronger the task-set representation becomes. Both accounts agree that disengaging from a highly-controlled task leads to the greatest switch costs, but notice how this creates contrasting predictions due to how these accounts define task strength. Yeung (2010) defines task strength by the automaticity of the stimulus-response mappings, which means that more control needs to be applied to weak task sets, which means it is harder to switch from weak tasks to strong tasks – the PASC. On the other hand, Umemoto and Holroyd (2014) define task strength by the control applied to the task, which means that applying more control to a task makes that task strong, which makes it harder to switch from strong tasks to weak tasks. Because this is the more intuitive direction (switching to a weaker task is harder), it is termed the *non-paradoxical asymmetrical switch cost* (NASC; Umemoto & Holroyd).

Umemoto and Holroyd (2014) found evidence of the NASC by having participants perform multiple phases of cued task switching. In phase one, the tasks were identical. However, in phase two, one task was systemically rewarded for accurate performance. Thus, the rewarded task was strengthened, and the non-rewarded task was weak in comparison. In phase three, the two tasks were, again, identical. They found a NASC pattern in the error rates – such that participants made significantly more errors when switching to the weak task than when

switching to the strong task. Their results also suggested that reinforcement persisted into phase three (where the tasks were identical), showing faster RTs and lower error rates when performing the previously-rewarded task. Umemoto and Holroyd interpreted these findings in favor of the HRL hypothesis, claiming that more control was applied to the reinforced task, which makes the reinforced task a strong task, which leads to a NASC pattern of error rates. This interpretation was bolstered by their phase three data, where – even though the tasks were of equal reward – residual top-down control for the previously-rewarded task enhanced performance on that task.

Umemoto and Holroyd (2014) take these results to be evidence against studies that found the PASC (Yeung & Monsell, 2003b; Yeung, 2010), and they argue that the HRL account is a better explanation of the switch cost in task switching than the TSI account. The problem is that both of these approaches make completely different assumptions regarding what constitutes task strength, and both their manipulations and interpretations critically rest upon these assumptions. Reconciling these assumptions renders these findings not necessarily incompatible. Consider that the strength of a task set is indeed defined by its stimulus-response mappings. The amount of control applied to the task only influences the activation of a task set, it does not directly alter its strength. Further, both accounts agree that control applied to a task persists after execution, and this control must be disengaged before performing a new task. When one task is more difficult than the other, the TSI account logic holds – the strength of the difficult task is weak, more control must be applied to execute the weak task, and it is harder to switch from the weak task to the strong task. When one task has a higher reward than the other, the TSI logic *still* holds. When a task has a high reward, a person will be more likely to exert control towards that task, regardless of its task strength (e.g., a person will exert more control towards performing a rewarded easy task than a non-rewarded easy task). Because more control is applied to a high

reward task, it is more difficult to switch away from. This illustrates how, all else being equal, the TSI account can explain a larger switch cost when switching from a high reward to a low reward task — the same effect that Umemoto and Holroyd (2014) claimed was damaging to the logic of the TSI account. But Umemoto and Holroyd's (2014) account is unable to explain the PASC when switching between two tasks of differential difficulty.

The goal of the Experiment 3a was to replicate the PASC using the same paradigm as Yeung (2010), thus providing more support for the TSI account. Experiment 3b then investigated the relationship between value and task set by varying the difficulty of the tasks. Because the TSI account makes strong predictions about the strength of the persisting activation of the task set depending on the difficulty of the task, varying the difficulty of the tasks could prove to be an ideal way to further investigate how persisting task set activation influences the relationship between task values and task selection. If PASCs are driven by a higher instantiation of the weaker task set while suppressing the stronger task set, and if the value of a task is closely integrated into the task set, there should be a large value sensitivity bias while executing the weaker task set. Specifically, there should be an increased sensitivity to the value of the highly instantiated task set (current task) along with a decrease in sensitivity to the value of the suppressed task set (other task). This bias would be largely neutralized while executing the stronger task set, as that task set is not as highly instantiated and the activation of the weak task set does not need to be suppressed.

Recall that Experiment 1 and 2 used shape and color tasks, while Yeung (2010) used shape and location tasks. We pilot tested these three tasks using a basic cued task switching procedure to ensure that the location task is indeed an easier task than both shape and color. This pilot test revealed that RTs are not significantly different across the shape and color tasks, but

RTs for the location task were significantly faster than both shape and color tasks. Therefore, given a successful replication of Yeung (2010) in Experiment 3a, Experiment 3b will integrate the point structure from Experiments 1 and 2 with the asymmetrical tasks of Experiment 3a to investigate the impact of task value and task difficulty on task selection and performance.

The primary goal of the present experiment was to replicate the findings of Yeung (2010). Participants were free to choose between two tasks of unequal difficulty, with the only instruction being to choose between the tasks equally often and in a random order. We expect to find between-task interference such that the representation of the weaker task set will be more highly instantiated than the representation of the stronger task set. For this reason, the weaker task set should be more difficult to inhibit following a task switch — consequently making it more difficult to switch from the weak task to the strong task. Empirically, this should result in larger switch costs when switching from the weak task to the strong task, and participants should exhibit a bias to repeat the weak task more often than the strong task. Additionally, between-task interference diminishes with increased preparation time (Yeung, 2010). Therefore, we predict that the PASC will be moderated by RSI, such that the between-task interference effects are more strongly present at short but not long RSIs.

Method

Participants

Participants were recruited from Lehigh University and participated in the experiment as an optional requirement for course credit. Participants were required to have normal or corrected-to-normal vision, and color vision. Data were collected from 17 participants. However, because participants in this experiment were instructed to choose between tasks randomly and equally

often, failure to switch tasks is an indication of not performing the task correctly. Therefore, five participants were excluded due to low switching rates (less than 15%). Participants were also excluded for high error rates (above 15%). Only one participant recorded error rates above 15%, however this participant was already eliminated due to switching rates lower than 15%. This left a total of 12 participants for final analysis.

Task

This experiment was intended to be a near replication of Yeung (2010; Experiment 1a). On each trial the judgment stimulus appeared in either the left, center, or right cell in a 3.97 cm X 1.32 cm grid that was presented in the center of a screen. The stimulus presented was a square, circle or rectangle with a black outline and no fill color. The location and shape of the stimulus varied randomly across trials. Participants were instructed to make either shape or location judgments on each presentation of a stimulus. Tasks were mapped to the “S”, “D”, and “F” keys for the left hand, and to the “J”, “K”, and “L” keys for the right hand. All responses for a task were mapped to either the left or right hand, and this mapping was counterbalanced across participants. Participants responded with index, middle, and ring fingers of both hands. For the shape task, circle was mapped to the leftmost finger, square to the middle finger, and triangle to the rightmost finger. Location was mapped to the corresponding finger, such that the left cell was mapped to the leftmost finger, middle cell to middle finger, and right cell to rightmost finger.

Each trial began with the grid (three columns and one row) presented centrally on the screen. The grid remained on the screen throughout the trial sequence. The stimulus appeared after either 1,100 ms or 200 ms. This interval varied between blocks in an ABBA order, which was counterbalanced across participants. The stimulus remained on the screen until the participant gave a response, at which point the trial sequence repeated (see Figure 11).

Procedure

After signing an informed consent form, participants practiced the tasks separately for 50 trials each. Participants then completed two practice blocks of voluntary task switching, both consisting of 50 trials each. We predicted that the PASC would be moderated at longer RSIs, and so one block contained short RSIs (200 ms), the other block contained long RSIs (1,100 ms); the order of the blocks was selected randomly. Participants were instructed to choose between tasks equally often and in a random order, as if flipping a coin on each trial to make task selections. After the practice blocks concluded and experimenters ensured that participants had no questions, participants performed 16 blocks of 90 voluntary task switching trials. Participants were encouraged to rest between blocks to reduce fatigue. Performance feedback was displayed after completion of each block. This feedback included error rate, average RT, number of shape and location judgments, and number of task switches and repetitions within each block. This feedback was provided to assist participants in ensuring that they were following directions appropriately (Yeung, 2010). After completing all 16 blocks, participants were debriefed and thanked for their participation.

Results

Data Cleaning and Coding

The same data cleaning and coding techniques used by Yeung (2010; Experiment 1a) were implemented in the analysis of the present experiment; these techniques only varied slightly from those used in Experiment 1. For analysis of the RT data, response repetition trials were eliminated. These were the trials where both the same stimulus from the previous trial repeated into the current trial, and participants repeated the same task that was performed in the previous

trial. Error trials and trials following error trials were also eliminated for the analysis of RT data. This resulted in 78% of total trials retained for analysis. Response congruence was determined by corresponding the spatial mappings of the shape task and location task. Specifically, a trial was coded as congruent when the spatial mapping of the location task matched the spatial mapping of the shape task. Therefore, congruent stimuli were as follows: circles in the left-hand cell, squares in the middle cell, and triangles in the right-hand cell. Mean RTs and error rates were analyzed using two 2 (task: strong vs. weak) X 2 (transition: switch vs. repeat) X 2 (RSI: short vs. long) X 2 (congruency: congruent vs. incongruent) within-participants ANOVAs. Task selection was analyzed by conducting a 2 (task: strong vs. weak) X 2 (RSI: short vs. long) on the proportion of task switches.

Task Strength

The location task was expected to be the stronger and more dominant of the two tasks. To ensure that this was the case, mean RTs and error rates were compared across the two tasks. The RT descriptive statistics are summarized in Figure 12 across transition, and task. Participants were faster when performing the location task ($M = 545$ ms, $SE = 36$ ms) than when performing the shape task, ($M = 670$ ms, $SE = 31$ ms), $F(1, 10) = 96.36$, $p < .001$, $\eta_p^2 = .91$. Participants also committed fewer errors when performing the location task ($M = 0.04$, $SE = 0.006$) than when performing the shape task, ($M = 0.08$, $SE = 0.01$), $F(1, 11) = 14.61$, $p = .003$, $\eta_p^2 = .57$. This suggests that these tasks did indeed differ in strength such that the location task is more dominant than the shape task. Additionally, participants were faster when responding to congruent stimuli ($M = 584$ ms, $SE = 29$ ms) than when responding to incongruent stimuli, $M = 612$ ms, $SE = 32$ ms, $F(1, 10) = 5.51$, $p = .04$, $\eta_p^2 = .36$. Error rates were also lower when responding to congruent stimuli ($M = 0.02$, $SE = 0.005$) than when responding to incongruent stimuli ($M = 0.06$, $SE =$

0.009). Further, there was a significant interaction of congruency and task on error rates, such that the impact of congruency was marginally stronger for the shape task than for the location task: participants' error rates were 0.05 lower when responding to congruent versus incongruent stimuli within the shape task, and this difference is only 0.02 within the location task, $F(1, 11) = 4.55, p = .06, \eta_p^2 = .29$. However, there was no significant impact of congruency on the relationship between task and RTs ($F < 1$). Additionally, the three-way interaction between task, transition, and congruency failed to reach significance for both RTs and error rates (all F s < 1), suggesting that the interaction described above for error rates did not change depending on whether the participant had repeated or switched tasks.

Task Strength and Task Switching

Participants responded significantly faster ($M_{Rep} = 571$ ms, $SE_{Rep} = 32$ ms, $M_{Switch} = 666$ ms, $SE_{Switch} = 42$ ms, $F(1, 10) = 21.66, p < .001, \eta_p^2 = .68$) and with fewer errors ($M_{Rep} = 5.64\%$, $SE_{Rep} = 1.00\%$, $M_{Switch} = 6.92\%$, $SE_{Switch} = 0.98\%$, $F(1, 11) = 12.64, p = .005, \eta_p^2 = .54$) when repeating tasks than when switching tasks. Critically, there was a marginally significant transition X task effect for RTs, such that participants exhibited a switch cost of 129 ms for the location task, and a switch cost of only 63 ms for the shape task, $F(1, 10) = 3.76, p = .08, \eta_p^2 = .27$. The direction of this effect is consistent with Yeung (2010), such that participants incurred a higher switch cost when switching to the stronger task than when switching to the weaker task (see Figure 12). However, this effect was reversed in the error rate data, with a numerically larger switch cost for the shape task (0.05) than for the location task (0.02) – although this trend was non-significant, $F(1, 11) = 2.55, p = .14, \eta_p^2 = .19$. Yeung (2010) observed that the transition X task interaction for RTs varied significantly across congruency; however, there was no such trend in the present data, $F < 1$.

Task Preparation

Increases in task preparation time are associated with decreases in switch costs, presumably because increased time allows for greater top-down control in inhibiting the interference of the previously used task set (Arrington & Logan, 2005; Allport & Wylie, 1999). Since increased switch costs when switching to an easier task is theorized to index between-task interference (Yeung, 2010), increased preparation time should moderate the interaction of task and transition on RTs. However, there is no evidence of a reliable three-way interaction of RSI, transition, and task on RTs in the present data, $F(1, 10) = 1.63, p = .23, \eta_p^2 = .14$. In fact, there are no main effects of RSI for either RTs or error rates (all F s < 1). There was, however, a marginally significant RSI by congruency interaction for RTs ($F(1, 10) = 4.7, p = .06, \eta_p^2 = .32$), suggesting that the RT cost for incongruent trials is greater with less preparation time (32 ms), and this cost decreases with added preparation time (23 ms).

Task Selection

To investigate whether there was a bias to repeat the weak task more than the strong task, a 2 (task: strong vs. weak) X 2 (RSI: short vs. long) was conducted on the proportion of task switches. There was a significant main effect of task ($F(1, 11) = 5.64, p = .04, \eta_p^2 = .34$), suggesting that there was a slight tendency to repeat the weak task to a greater extent ($M = .42, SE = .06$) than the strong task ($M = .43, SE = .06$). There was no main effect of RSI ($F(1, 11) = 3.38, p = .09, \eta_p^2 = .09$), nor was there an interaction between task and RSI ($F < 1$).

Experiment 3a Discussion

The crucial takeaway of the present experiment is the replication of Yeung's (2010) finding of larger switch costs when switching to the strong task than when switching to the weak

task — as evidenced in the present data by the significant interaction between transition and task on RTs. This suggests that the switch cost is indeed being driven by between-task interference in inhibiting the activation of the previously-relevant task set. In order to successfully perform the weak task, the weak task set must be highly activated while the strong task set is suppressed. When switching to the strong task set, the highly activated representation of the previously-relevant weak task set must be inhibited, and the previous suppression of the strong task set must be overcome. This scenario leads to larger switch costs than when disengaging from the strong task to perform the weak task.

It is worth pausing to consider the lack of significant response preparation effects in the present experiment. RSI did not significantly impact RTs or error rates, nor did it interact with any other factors in the model to influence these dependent variables. This suggests that participants are not responding to target stimuli faster after increased preparation than when preparation time is reduced. The lack of observed preparation time differences could potentially be due to the fact that RSI was manipulated between blocks. There is evidence to suggest that preparation manipulations are most robust when manipulated within blocks and within participants (Altmann, 2004). This trend is attributed to the control mechanism's "laziness", which will adopt a constant mode of responding when preparation time does not vary. A lack of preparation effects in the present study is puzzling because (a) the RSI manipulation was not between participants, and (b) Yeung (2010) found RSI effects using the same paradigm as reported above. It is possible that participants did not engage in increased levels of proactive control during blocks with longer preparation times.

However, given the successful replication of the PASC in Experiment 3a, Experiment 3b investigates how between-task interference influences the relationship between task values and task selections.

Experiment 3b

The present experiment served to further investigate the nature of the interaction between task set and task value representations. The rVTS paradigm from Experiment 1 was repeated in the present experiment with the tasks from Experiment 3a, which are asymmetrical in difficulty. This allowed for a more nuanced investigation of how the impact of task value on task selection is influenced by between-task interference.

Performing a weaker task necessitates a greater activation of that task set for successful performance, as evidenced by larger switch costs when switching from the weak task to the strong task in Experiment 3a. On the value-integration hypothesis, sensitivity to task value should be higher when there is more control being applied to activate the task set. Therefore, because more control is recruited to perform the weaker task set, sensitivity to the weak-task value should be highest while performing the weaker task. This is in contrast to value sensitivity while performing the strong task, which should be more well-balanced across the two values of the tasks. In other words, participants should be more sensitive to the value of the shape task than to the value of the location task while performing the shape task. However, there should be no bias between task values while performing the location task. Specifically, with respect to Figure 1, this would manifest as higher switch rates in the Current Change cell than the Other Change cell for the weak task, but equivalent across the Current Change and Other Change cells for the strong task. However, the evidence from Experiment 1 suggests that task value may be held in a separate representation from the task set. If this is the case, value sensitivity may not be

significantly different across the two tasks, as the control processes involved in resolving between-task interference might not directly interact with the relationship between task value and task selection.

It is also possible that value sensitivities may vary across the tasks, but in a different direction. If task value comparison competes with task set maintenance for control mechanisms, it follows that there may be more control resources available while performing the less resource-demanding strong task. This account makes the same prediction as the integrated value account when performing the strong task: task value comparison while performing the strong task should be more well-balanced across the two tasks. Conversely, exerting more resources to maintain the weaker task set may result in decreased resources available for task value comparison. If this is the case, there may be biases that emerge in value comparison as a result of failure to fully monitor and compare task values. This failure would be a direct consequence of insufficient control resources due to the increased control demands of performing the weak task.

Experiment 3b Method

Participants

Twenty five participants were recruited from Lehigh University to participate in this experiment. Participants had all of the same characteristics as the participants recruited for previous experiments, and also participated as an optional requirement for course credit. One participant surpassed the error rate threshold (15%) and was removed from the analysis. This left 24 participants for final analysis.

Task

The rVTS task used in the present experiment was nearly identical to that of Experiment 1 with one subtle, and crucial change: the tasks from Experiment 3a substituted for the tasks from Experiment 1. Therefore, we implemented the same reward structure as Experiment 1 with the same stimuli and responses as Experiment 3a and Yeung (2010). RSI was also manipulated in the same way as Experiment 3a, with either short (200 ms) or long (1,100 ms) RSI varied between blocks in an ABBA order, which was counterbalanced across participants (see Figure 13).

Procedure

Participants first practiced tasks separately for 30 trials each. The experimenter then introduced participants to the reward structure, and participants practiced rewarded voluntary task switching across two blocks of 30 trials each, one block for each RSI. Following practice, participants performed 12 blocks of rewarded voluntary task switching to 500 points each. Following each block, the time it took to complete the block was displayed on the screen; participants were encouraged to decrease their times as the experiment progressed.

Results

Performance Analyses

The same analyses that were conducted in Experiment 3a are performed in the present experiment for analyzing performance data, using a 2 (task: strong vs. weak) X 2 (transition: switch vs. repeat) X 2 (RSI: long vs. short) X 2 (congruency: congruent vs. incongruent) within-participants ANOVA for both RTs and error rates. The same data cleaning and coding methods that were implemented in Experiment 3a are used in the present analyses, resulting in retaining 66% of the original data for analysis.

Task Strength. Descriptive statistics for all cells of the design are displayed in Table 6. The location task was again the more dominant of the two tasks, with participants responding faster when performing the location task ($M = 564$ ms, $SE = 36$ ms) than when performing the shape task, $M = 722$ ms, $SE = 36$ ms, $F(1, 23) = 73.39$, $p < .001$, $\eta_p^2 = .76$. Participants also made significantly fewer errors when performing the location task ($M = 2.7\%$, $SE = 0.4\%$) than when performing the shape task, $M = 8.6\%$, $SE = 0.7\%$, $F(1, 23) = 55.39$, $p < .001$, $\eta_p^2 = .71$. Additionally, participants are faster when responding to congruent trials ($M = 626$ ms, $SE = 27$ ms) than when responding to incongruent trials, $M = 656$ ms, $SE = 30$ ms, $F(1, 23) = 22.82$, $p < .001$, $\eta_p^2 = .50$. Participants made significantly fewer errors when performing congruent trials ($M = 2.5\%$, $SE = 0.3\%$) than when performing incongruent trials, $M = 6.4\%$, $SE = 0.9\%$, $F(1, 23) = 48.56$, $p < .001$, $\eta_p^2 = .68$. Importantly, the impact of congruency on both RTs and error rates was contingent on the task that was performed. Participants were 39 ms slower when responding to incongruent than to congruent stimuli for the weak task, whereas this difference for the strong task was only 16 ms, $F(1, 23) = 7.55$, $p = .01$, $\eta_p^2 = .25$. This is further evidence for asymmetrical between-task interference such that the impact of incongruent stimuli is more costly when performing the weaker shape task than when performing the stronger location task.

Task Strength and Task Switching. Participants responded significantly faster when repeating tasks ($M = 626$ ms, $SE = 36$ ms) than when switching tasks, ($M = 743$ ms, $SE = 27$ ms), $F(1, 23) = 17.17$, $p < .001$, $\eta_p^2 = .43$. Additionally, participants make fewer errors when repeating tasks ($M = 5.4\%$, $SE = 0.6\%$) than when switching tasks, ($M = 6.4\%$, $SE = 0.6\%$), $F(1, 23) = 6.23$, $p = .02$, $\eta_p^2 = .21$.

Critically, this switch cost varies across tasks such that the switch cost for the weaker shape task is 75 ms, while the switch cost for the stronger location task is 148 ms, $F(1, 23) = 16.47, p < .001, \eta_p^2 = .42$ (see Figure 14). There was a similar marginally significant interaction for error rate data, showing that the increased likelihood to commit errors for task switches relative to task repetitions is greater for the stronger location task (2.1%) than for the weaker shape task, 0.2%, $F(1, 23) = 4.02, p = .06, \eta_p^2 = .15$. However, this interaction is not moderated by stimulus congruency for either RTs or error rates (all F s < 1). This suggests that the reduction in between-task interference associated with congruent stimuli is not robust enough to moderate the PASC.

Additionally, the main effect of transition varies across congruency for both RTs ($F(1, 23) = 11.13, p = .003, \eta_p^2 = .33$) and error rates ($F(1, 23) = 6.78, p = .02, \eta_p^2 = .23$), such that switch costs are 24 ms higher with 1.95% higher error rates for trials with incongruent as opposed to congruent stimuli.

Task Preparation. Participants responded significantly faster on trials with long RSIs ($M = 601$ ms, $SE = 26$ ms) than on trials with short RSIs ($M = 691$ ms, $SE = 34$ ms), $F(1, 23) = 79.72, p < .001, \eta_p^2 = .78$. There was no corresponding trend in the error rate data, $F(1, 23) = 1.80, p = .19, \eta_p^2 = .07$. The RT switch cost varied significantly by RSI ($F(1, 23) = 33.11, p < .001, \eta_p^2 = .59$) suggesting that there was a significant reduction in switch cost for long RSIs (54 ms) relative to short RSIs (218 ms). There was a similar (yet non-significant; $F(1, 23) = 2.67, p = .12, \eta_p^2 = .10$) trend in the error rate data, suggesting a decreased switch cost for long RSIs (0.6%) relative to short RSIs (1.8%).

There was also a significant interaction of task and RSI on RTs ($F(1, 23) = 5.3, p = .03, \eta_p^2 = .19$) suggesting that, when performing the strong task, participants are 110 ms faster on trials with long RSIs than on trials with short RSIs, whereas same difference is only 70 ms for the weaker shape task. There was a similar reliable pattern in the error rate data, $F(1, 23) = 7.65, p = .01, \eta_p^2 = .25$. Specifically, the benefit for longer preparation time results in a greater reduction of error rates when performing the location task (1%) than when performing the shape task (-0.4%). Additionally, there was a reliable interaction of task, congruency, and RSI on RTs, $F(1, 23) = 5.22, p = .03, \eta_p^2 = .19$. Specifically, the selective benefit for congruent stimuli while performing the shape task is only present with longer preparation time ($F(1, 23) = 3.23, p = .09, \eta_p^2 = .12$; although only marginally significant); for the short RSI, $F < 1$. Within the long RSI, the simple effect of congruency is significant for the shape task ($F(1, 23) = 11.12, p = .003, \eta_p^2 = .33$), but not for the location task, $F < 1$. This indicates that when performing the weak task on trials with long RSIs, participants respond significantly faster to congruent stimuli ($M = 665$ ms, $SE = 22$ ms) than to incongruent stimuli, ($M = 728$ ms, $SE = 24$ ms).

Reward and Task Selection

To analyze the impact of the reward structure on task selection, a 2 (current: constant vs. change) X 2 (other: constant vs. change) X 2 (task: strong vs. weak) X 2 (RSI: long vs. short) within-participants ANOVA was conducted on the proportion of task switches. However, due to the nature of the task transition outcome variable, the independent variable task was lag coded as the task performed at trial N-1. This was done in order to assess whether the difficulty of the task performed on the previous trial influences task selection on the current trial. Because the task that was performed on the *previous* trial is of interest when predicting task selections on the current trial, the independent variable “task” was lag coded at trial N-1.

Reward. Consistent with findings from both Experiment 1 and Experiment 2, there was a significant main effect of current ($F(1, 23) = 22.81, p < .001, \eta_p^2 = .50$), indicating that switch rates are higher when the current task decreased by one point from the previous trial ($M = .44, SE = 0.05$) than when the current task's value remained constant, ($M = .35, SE = 0.05$). There was also a significant main effect of other ($F(1, 23) = 17.96, p < .001, \eta_p^2 = .44$) indicating that switch rates are higher when the other task increased by one point from the previous trial ($M = .45, SE = 0.05$) than when the other task's value remained constant, ($M = .35, SE = 0.06$). There was a significant interaction of current and other ($F(1, 23) = 10.15, p = .004, \eta_p^2 = .31$), indicating that there is a larger increase in switch rates in response to relative shifts in the other task's value when the current task's value remained constant (.11) than to relative shifts in the other task's value when the current task's value decreased (.08; see Figure 15).

There was a main effect of task on switch proportions ($F(1, 23) = 8.81, p = .007, \eta_p^2 = .28$), indicating that there is a higher likelihood to repeat the strong task ($M = .39, SE = .06$) than the weak task ($M = .41, SE = .05$). This result stands in contrast to that from Experiment 3a and to the results of Yeung (2010), which both showed a repetition bias towards the weak task.

Additionally, there was a significant interaction of current and task ($F(1, 23) = 6.90, p = .02, \eta_p^2 = .23$), suggesting a greater increase in switch rates in response to changes to the current task's value after performing the strong task (.10) than after performing the weak task (.08). There was also a significant interaction between task and other ($F(1, 23) = 5.89, p = .02, \eta_p^2 = .20$), suggesting a greater increase in switch rates in response to changes in the other task's value after performing the weak task (.11) than after performing the strong task (.08). However, contrary to predictions, the three-way relationship between task, current, and other failed to reach significance, $F(1, 23) = 1.19, p = .29, \eta_p^2 = .05$.

However, planned comparisons between the Current Change and Other Change cells of the design (with respect to Figure 1) across tasks revealed a significant interaction, $F(1, 23) = 4.53, p = .04, \eta_p^2 = .16$. For the weak task, switch rates in the Other Change cell ($M = .43, SE = .06$) were slightly higher than in the Current Change cell, ($M = .40, SE = .05$). This trend was reversed for the strong task, with switch rates in the Other Change cell ($M = .39, SE = .06$) slightly lower than the Current Change cell, ($M = .41, SE = .06$). However, this interaction should be interpreted with caution as planned comparisons showed that the Current Change cell was not significantly different from the Other Change cell for either the strong task ($F(1, 23) = 1.27, p = .27, \eta_p^2 = .05$), or the weak task, $F(1, 23) = 3.54, p = .07, \eta_p^2 = .13$.

Reward and Preparation. Switching proportions were significantly higher on trials with long RSIs ($M = .43, SE = 0.05$) than on trials with short RSIs, $M = .36, SE = 0.06, F(1, 23) = 19.92, p < .001, \eta_p^2 = .46$. Importantly, the impact of RSI on switch proportions varied across levels of current ($F(1, 23) = 14.44, p < .001, \eta_p^2 = .39$), indicating that the current task decreasing by a point increased switch rates significantly more at long RSIs (.12) than at short RSIs (.06). There is a similar interaction between RSI and other task ($F(1, 23) = 14.56, p = .001, \eta_p^2 = .39$), indicating that there is a significantly larger increase in switch rates when the other task's value has increased by a point (relative to remaining constant) for long RSIs (.12) than for short RSIs (.07). These interactions converge to support the idea that added preparation time leads to more *optimal* increases in switch rates, and not just a general increase in switch rates overall.

Additionally, there was a marginally significant three-way interaction of RSI, current, and other, $F(1, 23) = 3.21, p = .09, \eta_p^2 = .12$. This trend suggested that the two-way interaction

of current and other was only significant for long RSIs ($F(1, 23) = 5.55, p = .03, \eta_p^2 = .12$); for short RSIs, $F < 1$. On trials with long RSIs, the simple effect of other is stronger when the current task remains constant (other constant: $M = .30, SE = .06$; other change: $M = .44, SE = .05$; $F(1, 23) = 90.16, p < .001, \eta_p^2 = .80$) than when the current task changes (other constant: $M = .45, SE = .05$; other change: $M = .54, SE = .05$; $F(1, 23) = 38.0, p < .001, \eta_p^2 = .62$).

Experiment 3b Discussion

The present experiment conducted a more nuanced investigation of the relationship between task values and task selections via the between-task interference effect. A weaker task set theoretically needs to be more strongly instantiated during execution. Therefore, if task value is integrated into the task set, there should be a bias to attend the value of the weak task after having performed the weak task, while the weak task set is still active. On the other hand, because a highly activated instantiation is not necessary for execution of the strong task, there should not be a bias to attend to the strong task's value after performing the strong task. Conversely, if task value comparison and task set maintenance draw from a common control resource, value sensitivity may vary across the tasks while performing the weak task, but in a non-specific direction.

Between-task Interference, Task Value, and Task Selection. The critical component of the present experiment involves investigating how the varying strength of between-task interference affects the relationship between task value and task selection. This investigation hinges upon the assumption that task set activation persists beyond task execution and influences execution of the subsequent task — an assumption that the PASC and congruency effect reported in the RT analyses converged to support. Therefore, analyzing differences in switch rates

between the Current Change and Other Change cells of the design across tasks should reveal whether there is a direct association between task value sensitivity and task set activation level.

Contrary to the value-integration hypothesis, this contrast revealed a higher tendency to attend the strong task's value while performing the weak task. However, consistent with the value-integration hypothesis, this contrast also revealed that value sensitivity did not vary significantly across tasks while performing the strong task. Therefore, these data do not support the overall notion that task value sensitivity is positively associated with task set activation; on the contrary, the present experiment suggests that this relationship may be negative in some contexts. However, this relationship must be interpreted with caution, as the effects are subtle. Nevertheless, the present series of experiments has revealed evidence to suggest that task value may not be dependent on task set activation, but rather dependent on the *control* mechanisms at work that manipulate the strength of the task set representations. In particular, evidence that increased preparation time is associated with more balanced value sensitivity suggests that less control demand for task maintenance might allow for more resources available for comparing task values. Additionally, the bias to be more sensitive to the strong task's value while performing the weak task is inconsistent with the value-integration hypothesis, but supports the shared-control account (albeit this account has a non-specific prediction about the direction of the bias while performing the weak task). This idea will be further expanded upon in the general discussion.

Finally, it is worth noting that there is not a bias to repeat the weak task in the present experiment, but rather a significant bias to repeat the strong task. This is in contrast to the findings of Yeung (2010), and is inconsistent with the idea that people are more likely to repeat the weak task because it is more difficult to disengage from. A potential explanation for this

inconsistent result is that, when instructed to earn 500 points as quickly as possible, participants are sensitive to the increased time demand of performing the weak task. Therefore, switching costs aside, when the tasks are of equal value, it is optimal to perform the strong task because it can be executed more quickly. For this reason, participants may have been persuaded to exploit longer runs of the strong task as opposed to the weak task. When this constraint on the environment is removed, and participants are instructed to choose between the tasks equally often and in a random order (as in Experiment 3a), the desire to avoid the effortful switch could take priority over avoiding longer RTs – yielding a repetition bias to the weak task.

General Discussion

The present series of experiments broadly investigated the interaction between task value and task set representation in predicting task selections in an rVTS environment. It was hypothesized that the value of a task might be integrated into, or be a feature of, its task-set representation – yielding a higher sensitivity to this value when the task-set representation is “active”. Findings across all three experiments generally did not support this prediction, in some cases suggesting the opposite trend – higher sensitivity to the value of the inactive task set representation. Overall, these data suggested that the task-value representation may be more separate from the task-set representation than originally anticipated. However, these data indicated that there was a bias to be more sensitive to the value of the inactive task set, suggesting that the representation of task set might not be completely independent from that of task value. Findings from these experiments are first discussed with respect to the original hypothesis. These findings are then reconsidered within a different framework – taking into consideration task selection, task execution, and the ways in which these processes influence each other.

Value as a Feature of the Task Set

The original question driving the present investigation was: how does representation of task reward interact with task-set representation to influence task selections in an rVTS environment? It was hypothesized that – when value is relevant for task performance – task value might be active in the task set representation, and thus there would be a greater sensitivity to the value of the active task set. This value-integration hypothesis offers the prediction that task selections should be driven to a greater extent by changes in value of the previously performed task than by changes in value of the non-previously performed task.

A pattern of results consistent with value being activated in the task-set representation was not observed in any of the three experiments reported in the present study. Experiment 1 provided an ideal environment to observe the impact of a value sensitivity bias on task selections, as both task values were displayed simultaneously with the target stimulus. If the predicted pattern of results were to be observed anywhere, it would be here. However, not only was there no increased sensitivity to value changes in the current task than to the other task in Experiment 1, this pattern was reversed, such that task selections were driven to a greater extent by sensitivity to the other task's value. An account postulating that task value is integrated into the task set fails to explain this pattern of results.

Experiment 2 utilized eye tracking to investigate both the impact of task values on eye movements, and the impact of fixations to task values on the task selection processes. On the value-integration hypothesis, there should have been a bias to attend to the value of the previously performed task on the current trial. Because there is evidence that task-set activation persists into the ensuing trial (Yeung, 2010), on this account, the persisting task-set activation should bias attention towards the active task-set's value on the ensuing trial. Following the logic

of the TSI, shifting sensitivity to the inactive task's value would involve disengaging from the active task set. If task value is represented in the task set, inhibiting the task set involves inhibiting task value. This would result in a bias to be more sensitive to the value of the active task set. However, no such bias emerged, as neither first fixations nor dwell proportions were significantly impacted by which task was performed on the previous trial. Dwell proportion, specifically, was influenced to a higher extent by value changes on the present trial. The lack of an impact of the active task set on fixation to task values could be due to the long RSI in Experiment 2, allowing the activation of the previously active task set to diminish. This could also explain why there was no bias between task values, as sensitivity to task values was evenly distributed between the current and other tasks.

Further, there was evidence that the impact of task values on task selections was mediated through dwell proportion. Because fixations were not biased towards the active task set, fixations could have solely reflected a value comparison process that was uninfluenced by the active task set. This interpretation is further reinforced by the fact that sensitivity to task values was equally balanced across the tasks in driving task selections in Experiment 2 (there was no increased sensitivity to value changes in the other task, as in Experiment 1). Balanced fixations in this context are consistent with work that suggests that eye movements index passive information acquisition (Bird et al., 2012; Nittono & Wada, 2009), whereby value comparison drives eye movements independently of the active task set. Task selections could have been driven by both the value comparison process, and increased preference due to the mere exposure (Kunst-Wilson & Zajonc, 1979). Mere exposure in this context would constitute developing increased preference for selecting the task associated with the value that was fixated for the longest period of time. It is possible that task selections were driven by a combination of task

value comparison and mere exposure, rather than by the active task set. This suggests that — while a task and its value may not be part of the same representation — representation of task and representation of value may indeed be linked in some way.

Finally, the results from Experiment 3b were in-line with the general finding from Experiment 1 – greater sensitivity to the value of the non-active task set. Strikingly, in Experiment 3b, this was only the case when executing the weak task set. Execution of a weak task set is associated with both higher instantiation of the weak task set representation along with suppression of interfering automatic activation from the strong task set representation (Yeung, 2010). Responses in this context are characterized by cognitive stability – maintaining higher focus on task execution (Shen & Chun, 2011). If task value is integrated into the task set, two overlapping predictions arise in this context. While performing the weak task, there should be higher sensitivity to the value of the active task set. Because cognitive stability is also characterized by better suppression of distractors (Shen & Chun, 2011), sensitivity to inactive task set value should be suppressed. However, while performing the weak task, there was higher sensitivity to the value of the inactive task set relative to the active task set. Additionally, while performing the strong task, less control is recruited to instantiate the task set, and responses should be less cognitively stable. In this context, sensitivity should be more well-balanced between the values of the tasks. This prediction was upheld, as sensitivity was equally distributed across task values while performing the strong task.

Overall, the value-integration hypothesis is unable to account for the present findings. There is no evidence to suggest that persisting activation from the active task set leads to increased sensitivity to the value of that task. On the contrary, when task values are

simultaneously displayed with the target stimulus, Experiments 1 and 3b reveal a tendency to exhibit increased sensitivity to the value of the inactive task set.

These findings have important implications for the nature of the task-set representation itself. There has been a lack of work directly investigating the nature of the relationship between the task-set representation and reward. Studies investigating the nature of the task-set representation largely focus on the stimulus-response mappings of the task, and how control mechanisms execute and switch between task-set representations (Yeung, 2010; Yeung & Monsell, 2003a). Meanwhile, studies investigating the role of reward in task switching have generally only considered the role of reward in altering the nature of cognitive control, with increases in reward considered to be associated with shifts towards proactive (Braver, 2012) and flexible modes of cognitive control (Shen & Chun, 2011). The present finding that task value is not part of the task-set representation is significant because it suggests that task value can only influence task-set activation indirectly via changes in cognitive control – as opposed to being a defining criteria of the task-set’s strength. For instance, a difficult, highly rewarded task can be performed efficiently because one has motivation to achieve reward, not because the task becomes easier per se. This is in-line with findings suggesting that performing a rewarded task will lead to shifts towards proactive control, thereby recruiting more top-down control (Chiew & Braver, 2014). Higher levels of control will increase the task-set’s activation, regardless of its initial strength. On the other hand, making the stimulus-response mappings of the task more automatic will directly increase the task-set’s strength (e.g., making location judgments with spatially compatible keys), thereby decreasing the demand for control. This is consistent with models of task switching that claim that the top-down goal and motivational components

associated with a task are dissociable from the procedural stimulus-response mappings used to execute the task (Gilbert & Shallice, 2002).

Before moving on to consider alternate interpretations of the present findings, it may be useful to consider a limitation of the present design. We postulated that task value might be represented in the task set *if* task value is a central component for task performance. This was motivated by findings in the literature suggesting the task set might be flexible in nature and activate features that are most important to the task at hand, rather than equally activating all possible features of a task (Wylie & Allport, 2000). For example, although all words are activated while word reading, the words that were read most recently receive the highest levels of activation (Allport & Wylie, 2000). It is possible that the information represented in the task set (such as the stimulus-response mappings) is *only* the information relevant for executing the task procedurally. While task value in the rVTS paradigm was relevant for task selection, it might not have been relevant for task execution per se. This distinction presses on whether task value was highly related to the accuracy and RTs of responses. Task value was indeed relevant to task execution in the larger context of blocks within the experiment – participants only received reward for correct responses, and they were motivated to complete each block as quickly as possible, thereby trying to minimize RTs on each trial. But the amount of reward received on each trial was unrelated to how fast the response was on that trial. This is in contrast to paradigms that associate reward with fast and accurate responses in task switching contexts (Kleinsorge & Rinkenauer, 2012). The main problem with evaluating whether value is part of the task set in these paradigms is that value is not systematically tied to task, but rather manipulated independently (i.e., a trial can either be high or low reward, and a trial can either be a repetition or a switch). It is possible that value can indeed be represented in the task set, but only when

reward is sufficiently relevant to the execution of the task. In order to explore this possibility, it would be necessary to both systemically associate value with task, and make the reward directly relevant for execution of the task. For example, each task has its own value, and this value is only acquired when the task is performed faster than some threshold. It would be interesting to see whether – under these conditions – value would be represented in the task set and thus drive attention towards the value of the previously performed task.

Nevertheless, it may be more useful to consider the impact of value and control on task switching within the larger framework of task selection and task execution. Task selection and task execution are thought to exert bidirectional influences on each other (Gilbert & Shallice, 2002), although the extent of this influence remains largely unknown (Poljak & Yeung, 2012). The remainder of the discussion will first consider the influence of task value on task execution, followed by investigating the influence of task execution on task selection.

Task Value, Cognitive Control, and Task Execution

The present findings may be able to shed some light on a theoretical debate in the cognitive-control literature. The influence of reward on cognitive control has been characterized in several studies (Chiew & Braver, 2014; Locke & Braver, 2008; Shen & Chun, 2011). However, there is a debate as to the nature of the relationship between control and the task set: does the level of control define task-set strength, or is task-set strength a factor that influences how much control is recruited? The widely accepted view in the cognitive control literature is the latter – a strong task is easier to perform and requires less control resources to execute (Yeung, 2010; Yeung & Monsell, 2003a). However, Umemoto and Holroyd (2014) claim the opposite – control is a defining feature of task strength, and more control resources make the task set

stronger and easier to perform. These contrasting views are first outlined, followed by a post-hoc investigation of the present data that speaks to this debate.

Task Strength and Control. The critical distinction between Yeung's (2010) and Umemoto and Holroyd's (2014) accounts of task-set strength rests on how cognitive control influences the task-set representation. For Yeung (2010), the level of control over task execution could temporarily modulate the activation of the task set, rather than modulating the strength of a task set itself. More difficult tasks recruit more effortful control for successful execution, thereby temporarily increasing the activation of the task set and the automaticity of the stimulus-response mappings. This suggests that two task sets can vary in strength at baseline (e.g., one task is more difficult than the other), but performance on the two tasks can be more closely matched by increasing the amount of control applied to the difficult task, thereby making the stimulus-response mappings temporarily more automatic than they were at baseline. However, a highly activated difficult task set does not change the strength of the task set itself – it is still a weak task, because it is difficult. An easy task's set is still stronger relative to that of a difficult task, despite more effortful control being applied to the difficult task.

For Umemoto and Holroyd (2014), the level of control recruited to execute a task is a defining feature of the task-set strength. If a participant is performing a task quickly and accurately, the task-set strength is strong, and it must be because the participant is recruiting more control to perform the task. Regardless of whether the task has a greater reward associated with it, or it is just easier to perform, enhanced performance is due to increased control, which makes the task-set strong.

Control and the Switch Cost. What predictions do these competing interpretations make regarding the switch cost? Both Yeung (2010) and Umemoto and Holroyd (2014) embrace a

mechanism from the TSI account to explain switch costs – switch costs are primarily driven by the process of fully disengaging control from the previous task in order to switch a different task. Their predictions regarding the switch cost differ based on their notions of the relationship between task strength and control. Yeung (2010) assumes that *less* control is used to execute a strong task set, while Umemoto and Holroyd (2014) assume that *more* control is used to execute a strong task set. Thus, Yeung (2010) predicts greater switch costs when switching away from a weak task set (where more control is applied, PASC), while Umemoto and Holroyd (2014) predict greater switch costs when switching away from a strong task set (where more control is applied, NASC).

Another important distinction between these competing accounts is their implications for manipulations to task strength and cognitive control. These accounts generally agree upon the influence of reward on cognitive control – increased reward leads to more recruitment of cognitive control. The accounts differ with respect to how manipulations to stimulus-response automaticity influence control. Yeung’s (2010) account predicts an interaction between difficulty and reward, such that the switch cost will be highest when switching from a high-reward, difficult task (where the most control is recruited) to a low-reward, easy task. However, because increases in reward are associated with proactive control (Chiew & Braver, 2014), and proactive control attenuates persisting task-set activation (Yeung & Monsell, 2003a), the switch cost should be small when switching to a high-reward task — regardless of whether switching *from* an easy or difficult task. Conversely, Umemoto and Holroyd’s (2014) account posits that the switch cost will be highest when switching away from a high-reward, easy task (where the most control is recruited) to a low-reward, difficult task. However, because this account posits that difficulty and reward have overlapping impacts on control, it predicts that switch costs should be

smaller when switching to a high-reward task, but that the cost of switching from an easy task will still be significantly higher than switching from a difficult task.

Post-hoc Investigation. Given that Experiment 3b uses both reward and difficulty manipulations, it is worthwhile to look for these manipulations' different contributions to the switch cost. A post-hoc analysis was conducted on Experiment 3b data to investigate the interaction between task value and task difficulty on switch costs (this analysis is reported in full in Appendix B). This analysis revealed that, for the difficult task, there was no relationship between task value and switch cost. However, for the easy task, the switch cost increased dramatically as the task decreased in value. These results are largely in-line with Yeung's (2010) interpretation of the TSI account. When TSI is high (while switching from the difficult task to the easy task), switching to a high value task increases preparatory and flexible control to more effectively inhibit TSI and reduce the switch cost. Further, it is possible that, because switching to the difficult task from the easier task is an easier course of action, responses in this context are at ceiling and unaffected by reward (see Figure 16).

However, due to the overarching context of the experiment, this interpretation must be taken with caution. Participants were instructed to accumulate a set amount of points as fast as possible. Therefore, switching to a lesser valued task incurs an added time cost for less value. This action is at odds both with gaining reward and doing so quickly – the two main objectives for participants in rVTS. Increased switch costs for the easy task at low value relative to high value could simply be the product of an error detection signal partially inhibiting the procedural response. It has been suggested that high order prefrontal cortex (PFC) areas modulate sensory-to-motor pathways, and that influences from the PFC serve an inhibitory role to override automatic motor responses (Miller & Cohen, 2001). Slowed RTs when switching away from

reward could reflect PFC influences inhibiting but failing to override the automatic motor response. Because the present paradigm was designed to investigate how the impact of value sensitivity biases across tasks influences task selections, task value and the switch cost are confounded – there will never be a context where switching away from a higher valued task is a rational choice. Further, because the difference between task values was codependent upon task selections, observations at more extreme ends of the point difference were sparse — particularly observations where participants switched away from a more highly rewarded task. Nevertheless, the present study found cursory, serendipitous evidence of an interaction between task difficulty and task value predicting switch costs. This supports the idea that task difficulty directly influences task strength, while task value influences the nature of cognitive control.

The Influence of Task Execution on Task Selection: Drawing from a Shared-Control Mechanism

The influence of task execution on task selection is more uncertain than the influence of task selection on task execution. This is partially due to the fact that voluntarily choosing a task is a relatively new feature of the task switching literature (Arrington & Logan, 2004), and that cognitive control researchers are generally more interested in the processes that influence task performance over task choice (Schiffer, Waszak, & Yeung, 2015). However, this does not preclude the consideration of top-down goals in cognitive control (Gilbert & Shallice, 2002), only the consideration of how these factors impact task selection.

This is not to say that the topic of task selection is neglected altogether. On the contrary, studying task choice in VTS has yielded useful insights into the task-choice process. When instructed to perform tasks equally often and in a random order, participants tend to repeat more often than switch tasks (Arrington & Logan, 2005). Arrington and Logan (2005) suggest that the

intent to select tasks according to a random sequence could reflect an executive process, where a random response must be computed from the representation of recent responses held in working memory (Baddeley, 1996). From this perspective, task selection could be the product of an interaction between the executive processes of maintaining task goals and switching between tasks. This is consistent with the parallel distributed processing (PDP) model of task switching (Gilbert & Shallice, 2002), which would attribute the repetition bias to a failure of top-down control to override the active task set's influence to repeat.

What, then, might the task selection process look like in rVTS? Decision making models (specifically ones that posit effort as a cost) may be the most informative in addressing this question. There is evidence to suggest that comparing representations of value to compute a decision can be influenced by shifts in both attention and effort: people's preferences for an option are inflated the longer that option is fixated (Krajbich et al., 2010), and people place a larger value on effort after effort has been expended rather than before (Kool & Botvinick, 2014). This suggests that the executive process of comparing task values is influenced by bottom-up factors inherent to the task-value-comparison process; people attempt to objectively weigh decision options, but this attempt is influenced by the trial-by-trial cognitive demands of the environment. Task selection and task execution are analogous in this respect: there is a top-down goal that must compete for control over the bottom-up influences of the environment.

People compare values to make decisions, but what is actually being compared in rVTS? It is more complicated than just comparing the values of the two tasks. On each trial, participants must quickly determine which task will yield the highest reward at the lowest time cost. As outlined in the introduction, this process involves manipulating a representation of the amount of effort needed for a task and subtracting it from the reward for that task. Further, the evidence

outlined above suggests that this comparison process is susceptible to bottom-up influences inherent to the comparison process itself, such as low-level perceptual features of stimuli capturing attention. Even further, the executive process of task selection is in competition with the executive process of task execution, and effects such as the repetition bias suggest that the impact of task execution on task selection is non-trivial. The picture of task selection in rVTS is now looking quite complex.

The present data can speak to a fraction of this complexity. My hope for the present discussion is to shed as much light on the complexity as possible, while outlining concrete avenues for future research to tackle this complexity both theoretically and empirically.

Task Selection as an Executive Process. Since task selection can be characterized as its own executive process, with competition between goal-driven factors and bottom-up influences from the environment, it is worthwhile to consider some of the observed effects in the decision making literature within a top-down versus bottom-up framework. Recall that the decision making effects that are of interest to the present discussion are typically observed in forced dual-choice paradigms, where participants are presented with two choice options (e.g., food) and instructed to select the option that is most preferable (Krajbich et al., 2010). People will tend to attend to options that are most important in making the decision (the utility effect), and this provides the most prominent example of goal-driven behavior in such a dual-choice context (Fiedler & Glockner, 2012; Glockner & Herbold, 2011). For example, when presented with two food options, people will attend to the one that they think is preferable. In this case, selections closely approximate preference ratings at baseline, which is thought to reflect “rational” choice. It is possible that deviations from rationality in this context could be considered bottom-up influences of the environment that drive decisions away from what was considered preferable at

baseline. This can occur when attention is captured by factors unrelated to the goal-driven aspect of the experiment. For example, attention can be captured by low-level features of the stimuli (Glockner & Betsch, 2008), and sustained attention towards an option can inflate preference for that option above baseline (Krajbich et al., 2010). This could lead participants to make selections that are inconsistent with their baseline preferences, which would be considered irrational from a decision-making standpoint.

How do these top-down and bottom-up factors play out in rVTS? It might be most useful to compare Experiment 1 against Experiment 2, since there were subtle design differences that led to surprising differences in results. The most notable difference in results between experiments was that there was a bias to be more sensitive to the other task's value in Experiment 1, whereas there was no such bias in Experiment 2. As previously discussed, one possible source for this difference in results could be due to the way the values were displayed on the screen across the two experiments.

In Experiment 1, values were visible throughout the whole trial, thereby making a change in value visually salient. In Experiment 2, values were not visible until fixated. The visual saliency of changing values in Experiment 1 might have served as a bottom-up captor of attention where – in cases where only one of the task values had changed – attention would be automatically drawn to the changed value (Glockner & Betsch, 2008). Preference could have then been facilitated for the task associated with the fixated value due to mere exposure (Kunst-Wilson & Zajonc, 1979), leading increases in the other task's value to become more attractive and decreases in the current task's value to become less aversive. This would explain how such a bottom-up effect (attention being captured by the saliency of a changing digit) would lead to increased switch rates when only the other task's value has increased versus when only the

current task's value has decreased. In Experiment 2 value change was not as immediately salient. Task values were only revealed when attention was explicitly directed to the value's location on the screen, thereby eliminating the visual saliency of a change in value. The fact that the bottom-up influence on preference was removed might explain why sensitivity between task values seemed more well-balanced in Experiment 2.

Experiment 2 also introduced the “value search period,” which allowed participants a full second before the onset of the target stimulus to view and compare task values. Results indicated that almost all participants accessed both values on most trials, suggesting that participants utilized this time to compare the values between the tasks. This raises the possibility that the bias to be more sensitive to the other task's value in Experiment 1 could be due to between-task interference (Yeung, 2010). Having more time between trials would allow for top-down control to resolve the between-task interference, thereby leading to more balanced sensitivity across the values of the two tasks. The idea that added preparatory time is associated with increases in top-down control is consistent with evidence suggesting that both the repetition bias and the switch cost diminish with more time to prepare for the upcoming task (Arrington & Logan, 2005). Although it is difficult to distinguish whether the bias towards the other task in Experiment 1 was a result of the bottom-up, value-change saliency or due to between-task interference, it is worth taking a closer look at what the between-task interference effect might look like in rVTS.

The Impact of Task Execution on Task Selection. Between-task interference is the phenomenon whereby inhibiting the activation of a no-longer-relevant task set has negative consequences for executing a new task. What are some ways that this effect can explain the increased sensitivity to changes in the other task's value in Experiment 1? If task value was represented in the task set (which our data suggest that it is not), we would expect that between-

task interference would result as a bias to be more sensitive to the value of the active task set. But it is possible that task execution can influence ensuing task selection in other ways as well. If task execution and task selection both rely on cognitive control, it is possible (if not likely) that these processes compete for control resources. If control resources need to be allocated between these two processes, it would predict that allocating resources to one process would come at the expense of resources available for the alternative process. Such competition for resources is common in contexts where two executive processes are active at once (Pashler, 1994). This notion is further supported by the finding that both task selection and task execution benefit from longer preparation intervals (Arrington & Logan, 2005).

Therefore, a shared-control account of task selection and task execution would posit that these two processes draw from a common-control mechanism. When there is a sufficient amount of preparatory time between these processes – and they are not competing for control resources – control can be solely devoted to the active process. With sufficient preparation, control in task-selection may be more adept at comparing value and effort representations, while suppressing irrelevant information. This was potentially the case in Experiment 2. Participants had a long time to compare task values following the execution of the previous task. This extra preparatory time could have allowed participants to disengage control from task execution and apply control to task selection, which could have allowed for better instantiation of the task instructions and better inhibition of task-irrelevant features. Higher levels of control devoted to task selection could result in more symmetrical sensitivity to task values. In short, having more time to recover from the previous task could lead to better decision making in the following trial. This interpretation assumes that more balanced sensitivity to task values indicates better control –

since there is no reason to believe that attending to one task's value over the other would result in more efficient performance, this assumption seems viable.

How does this account explain the pattern of results in Experiments 1 and 3b? In these experiments, there is less preparatory time between task execution and task selection, theoretically straining control resources. Disengaging control from task execution to perform task selection is difficult, and without sufficient time for control to be disengaged there could be negative consequences for the task-selection process. This could lead to bottom-up influences corrupting the task-selection process, and task selections would be affected by task-irrelevant features. This would explain why value sensitivity was biased in Experiment 1 – participants had less time following task execution to inhibit control from the active task set, consequently there was a lack of control available to compare task values and an inability to suppress task-irrelevant information. This interpretation is also supported by the results of Experiment 3b. There was a value-sensitivity bias after performing the weak, but not the strong task. In-line with the TSI account, it is more difficult to disengage control from a weak task than it is to disengage from a strong task. Therefore, after performing the weak task, control was strained, and value sensitivity was biased as in Experiment 1. However, after performing the strong task, control is easily disengaged and applied to task selection, and value sensitivity was balanced as in Experiment 2.⁶

⁶ Such a shared-control account is inconsistent with the non-significant correlation between individual differences in switch cost and performance efficiency in Experiment 1. If effort for task execution adversely affected task selection, those who need to exert more effort in task execution should exhibit less efficient task selections. The relationship between switch cost and performance efficiency might have been more clear had there been a more objective measure of performance efficiency, thus we still consider the shared-control account to be a viable interpretation of the effects throughout these experiments, even in spite of the non-significant correlation between individual differences in switch cost and performance efficiency.

The primary underlying assumptions of this interpretation are twofold: (a) insufficient control available for task selection results in asymmetrical sensitivity to task values, and (b) the asymmetry manifests as increased sensitivity to the other task's value. These assumptions are worthy of further investigation. At present – from a shared-control perspective – it is unclear why participants would be biased to attend to the other task's value.

It is possible that there is a bottom-up influence to attend to the features of a more difficult choice. While this hypothesis has not been directly investigated in the literature, it would explain the trend to be more sensitive to the value of a difficult switch. While Kool and Botvinick (2014) demonstrated that the value of effort increases as more effort is expended, they did not investigate whether the rising value of effort is associated with increased attention to that value. If attention is naturally drawn to more effortful choices, it could explain why – in contexts of strained control – there is increased sensitivity to changes in the other, rather than the current task.

Another assumption of the shared-control account is that failure to fully disengage control from task execution results in more bottom-up interference in task selection. However, there is evidence that persisting interference from task execution could alter the top-down *intention* to select tasks (Poljac & Yeung, 2012), rather than just decreasing the strength of the top-down intention. Evidence for this comes from dissociable electroencephalogram (EEG) components associated with both task execution and task selection, suggesting that between-task interference can impair the ability to form effective task intentions. Although it remains unclear whether task intentions in this case represent the intent to select a task, or the preparatory intention to execute a task (Poljac & Yeung, 2012).

The complexity of decision making in task switching is primarily because of the uncertainty surrounding the timing of task-set inhibition, task selection, and task execution. There is a debate as to whether the persisting activation of the task set simply dissipates over time, or needs to be actively suppressed in order to disengage control (Allport et al., 1994; Rogers & Monsell, 1995). It is possible that disengaging control could be the result of both active and inactive processes – when control is demanded quickly after execution, inhibition could facilitate the task set dissipation. Evidence that disengaging from a task set is at least in part an active process comes from the finding that increases in preparatory time do not always result in better performance. Performance at long RSIs is typically better when RSI is varied within blocks, and this is thought to be because participants do not actively inhibit persisting task-set activation when the same preparatory time is given over many consecutive trials (Yeung & Monsell, 2003a). In sum, it is difficult to understand how the decision making processes in task switching influence each other because they are almost impossible to index behaviorally. Future work should look for other (neural) markers of these processes, or utilize a double-registration paradigm (Arrington & Logan, 2005), which has separate stimulus-response mappings for task selection and task execution. Once the timing of these processes is better mapped out, it will be easier to understand how control is shared between them.

Future Work

The present research has merely scratched the surface of the interaction between value representation and the task set in dynamic environments. The notion of a parsimonious model of this interaction, where task value is integrated into the task set, is discounted based on the present evidence. Therefore, future research should continue to investigate the relationship between

value and task execution / task switching from a perspective that maintains value and task set as separate representations.

One main suggestion for future paradigms investigating this relationship is to independently manipulate the task values from task selections. This change would make it easier to investigate behavior across many levels of the difference in value between the tasks. When task values are systematically tied to task selections, participants tend to respond in ways that keep the tasks relatively close in value (e.g., no task value is likely to be more than three points larger than the other task's value). Therefore, there were not enough observations at extreme values of the point differential to analyze task selection patterns across each level of the reward structure (rather observations below -4 and above 4 were grouped together). By randomly generating task values between one and ten on each trial, participants would be forced to confront situations where one task value is much higher than the other. They would also be less able to predict what the values will be on the next trial. This simplification would come at the expense of a portion of the strategic component of the paradigm. However, even with task values manipulated independently from task selections, participants still need to strategically make task selections in a way to maximize value receipt and minimize time costs – which is the central focus of the present investigation. Independently manipulating value from choice might make it easier to disentangle the influences of reward and difficulty on task selections.

Moreover, the interaction between task value and task difficulty on switch costs is also confounded by the relationship between rVTS instructions and the voluntary nature of task selections in this paradigm. In rVTS, participants are instructed to earn 500 points as fast as possible within each block. Imagine a scenario where a participant has just performed a task worth seven points, while the other task is worth four points. As the task that was just performed

is still worth more than the other task (which it certainly will be in this scenario) it is faster and more profitable to repeat the task again. Because it often does not make sense to switch tasks in situations like this, there are not many trials where it occurs. Therefore, investigating this relationship may be better served by implementing an even simpler paradigm, one akin to rewarded cued task switching. A cued task switching paradigm that manipulates both task value and task difficulty, with reward receipt contingent upon both fast RTs and accurate responses, creates an environment where switching away from a higher value task is not at odds with the overarching goal in the experiment. This would also serve as a more well-balanced design, where observations would be parametrically distributed across all conditions. This would be an ideal context to investigate the impact of difficulty and value on performance, which would be completely isolated from the selection process.

Conclusion

The present study broadly investigated how representation of value interacts with the mechanisms involved in selecting and executing tasks to influence decisions in a dynamic environment. This investigation was motivated by the overarching goal to further integrate concepts from the decision-making literature (e.g., computing decisions from weighing value against effort costs) with the mechanisms from the cognitive control literature — theorized to underlie executing and switching between task sets. Findings from the present experiments collectively demonstrate a lack of support for the notion that representation of task value is incorporated into the task set representation itself. It is evident that the process of comparing task values interacts with the process of manipulating task sets to influence task selections, but the nature of this interaction remains largely unclear. Future work should investigate why there is increased value sensitivity to the inactive task-set's value, and further clarify the timing of the

decision processes involved in task switching. Illuminating these mechanisms may clarify the role of control in task selection, specifically in the complex context of rVTS. Nevertheless, the present study provides useful preliminary insights by integrating theories from disparate — but conceptually similar — fields, and outlines clear avenues for future theoretical development. The interaction between value and control is complex, but it is paramount to understanding human decision making in dynamic environments.

Table 1

Descriptive Statistics (Means and Standard Errors) for Switching Proportion by Condition for rVTS in Experiment 1

	Other Constant	Other Change
	<i>M (SE)</i>	<i>M (SE)</i>
Current Constant	.23 (.03)	.43 (.03)
Current Change	.39 (.03)	.49 (.03)

Table 2

Descriptive Statistics (Means and Standard Errors) for Response Time (ms) by Condition for Cued Task Switching in Experiment 1

	Repeat	Switch
	<i>M (SE)</i>	<i>M (SE)</i>
Long Cue-Target Interval	667 (45)	810 (50)
Short Cue-Target Interval	1025 (68)	1082 (58)

Table 3

Model Parameters (odds ratios) for the Best Fitting Generalized Linear Mixed-Effects Model of Probability of Switching by Reward Condition in Experiment 1

	Beta Estimate (SE)	z-value
Intercept	0.20 (1.19)	-9.27***
Current	1.75 (1.12)	5.26***
Other	2.69 (1.12)	9.27***
Difference	2.29 (1.20)	4.64***
Current X Other	0.60 (1.05)	-9.80***
Current X Difference	1.05 (1.02)	3.43***
Other X Difference	1.01 (1.01)	0.74
Current X Other X Difference	1.00 (1.02)	0.07

*** $p < .001$.

Table 4

Proportions of Fixations to Task Values by Fixation Strategy and Participant in Experiment 2

Participant ID	Fixate Both	Fixate Neither	Fixate Current	Fixate Other	Total Trials
1	.85	.04	.07	.03	379
2	.98*	0	.007	.01*	401
3	.75	.07	.10	.09	421
4	.94	.04	.01	.01*	426
5	.85	.07	.06	.02*	289
6	.75	.03	.07	.15	373
7	.42	.26	.16	.16	374
8	0*	.79*	.06	.16	140
9	.005*	.35	.047*	.17	216

10	.86	.04	.04	.06	468
11	.94	.01	.03	.03*	360
12	.30	.18	.31*	.22*	362
13	.29	.40*	.16	.16	245
14	.62	.01	.18	.19*	358
<hr/>					
Overall <i>M</i> (<i>SD</i>)	.61 (.35)	.16 (.22)	.12 (.13)	.10 (.08)	343.71 (90.23)
<hr/>					

* More extreme than 1 *SD* from the overall *M*

Table 5

Model Parameters for the Best Fitting Generalized Linear Mixed-Effects Model of Probability of Switching by Reward Condition in Experiment 2

	Beta Estimate (<i>SE</i>)	z-value
Intercept	-0.21 (1.25)	-7.123***
Current	3.32 (1.36)	3.90***
Other	3.46 (1.34)	4.23***
Dwell	0.24 (1.27)	-5.89***
Current X Other	0.72 (1.25)	-1.50
Current X Dwell	1.80 (1.39)	1.82†
Other X Dwell	1.17 (1.38)	0.61
Current X Other X Dwell	0.66 (1.55)	-0.94

*** $p < .001$. † $p < .1$.

Table 6

Descriptive Statistics (Mean and Standard Errors) for Response Time (ms) and Error Rates by Condition in Experiment 3b

	Response Times			
	Incongruent – Repetition	Incongruent – Switch	Congruent – Repetition	Congruent – Switch
	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>
Location Task – Short RSI	574 (55)	829 (35)	568 (46)	798 (39)
Location Task – Long RSI	493 (34)	578 (30)	498 (38)	558 (26)
Shape Task – Short RSI	752 (32)	941 (30)	754 (43)	893 (38)
Shape Task – Long RSI	741 (31)	753 (24)	668 (27)	680 (20)

Error Rates

	Incongruent – Repetition	Incongruent – Switch	Congruent – Repetition	Congruent – Switch
	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>	<i>M (SE)</i>
Location Task – Short RSI	.02 (.005)	.07 (.01)	.02 (.005)	.04 (.02)
Location Task – Long RSI	.02 (.005)	.04 (.005)	.01 (.003)	.01 (.005)
Shape Task – Short RSI	.10 (.01)	.11 (.01)	.04 (.01)	.03 (.008)
Shape Task – Long RSI	.11 (.01)	.13 (.02)	.04 (.008)	.02 (.005)

	+	Other	0
Current	-	S_R Both Change	SR Current Change
	0	SR Other Change	sR Neither Change

Figure 1. Predictions for the four cells of the reward structure. Current represents the previously performed task, other represents the non-previously performed task. The “-“ sign indicates a loss of one point from the previous trial, the “+” sign indicates a gain of one point from the previous trial, and a “0” indicates no change in point value. The size font for “S” and “R” corresponds to the likelihood to either switch or repeat tasks, respectively.

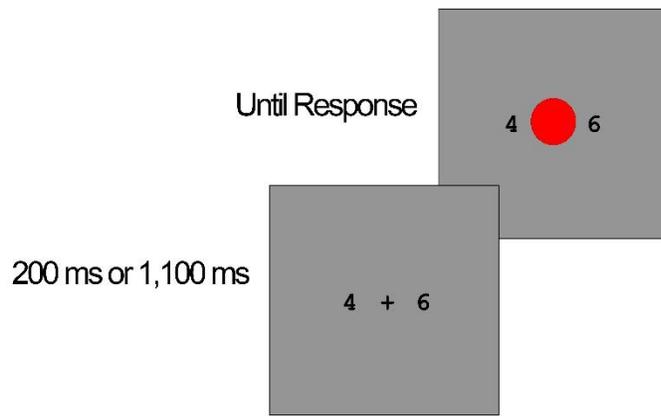


Figure 2. Experiment 1 rVTS trial sequence.

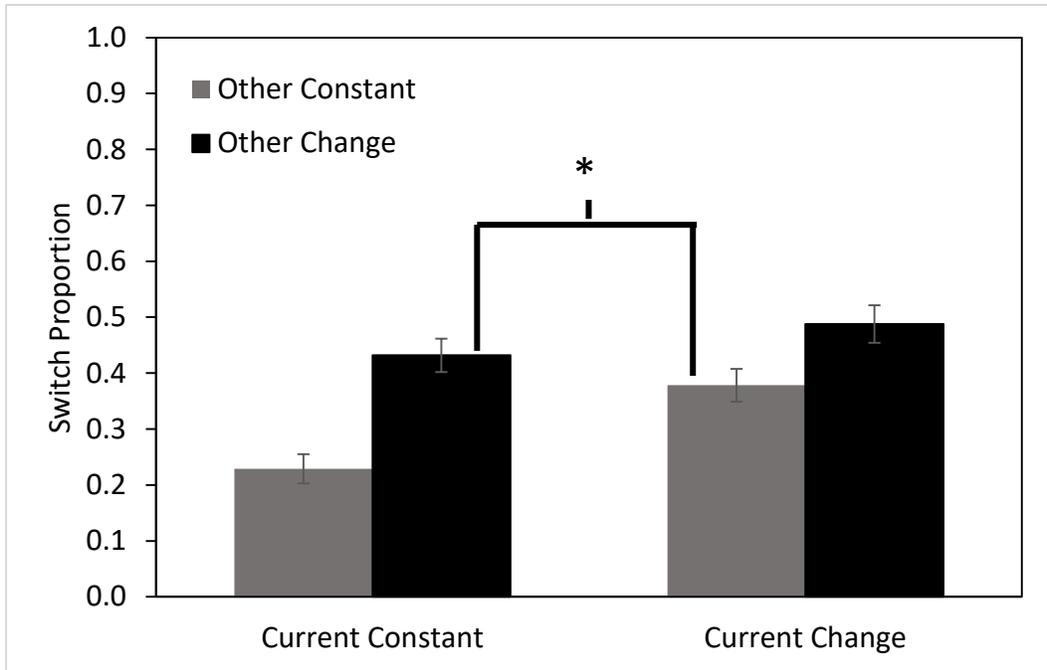


Figure 3. Mean switching proportion by reward condition from Experiment 1. Constant indicates that the point value has remained the same from the previous trial. Other change indicates that the other task's value has increased by a point from the previous trial, while current change indicates that the current task's value has decreased by a point from the previous trial. Error bars reflect standard errors.

* $p < .05$

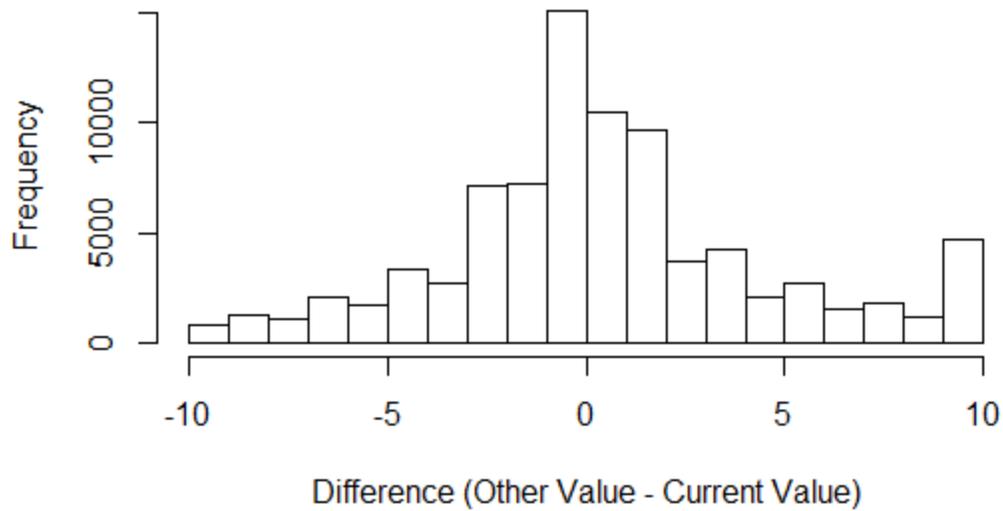


Figure 4. Histograms of observations along the Difference variable in Experiment 1. Negative differences indicate trials where the current task’s value is greater than the other task’s value; positive differences indicate trials where the other task’s value is greater than the current task’s value.

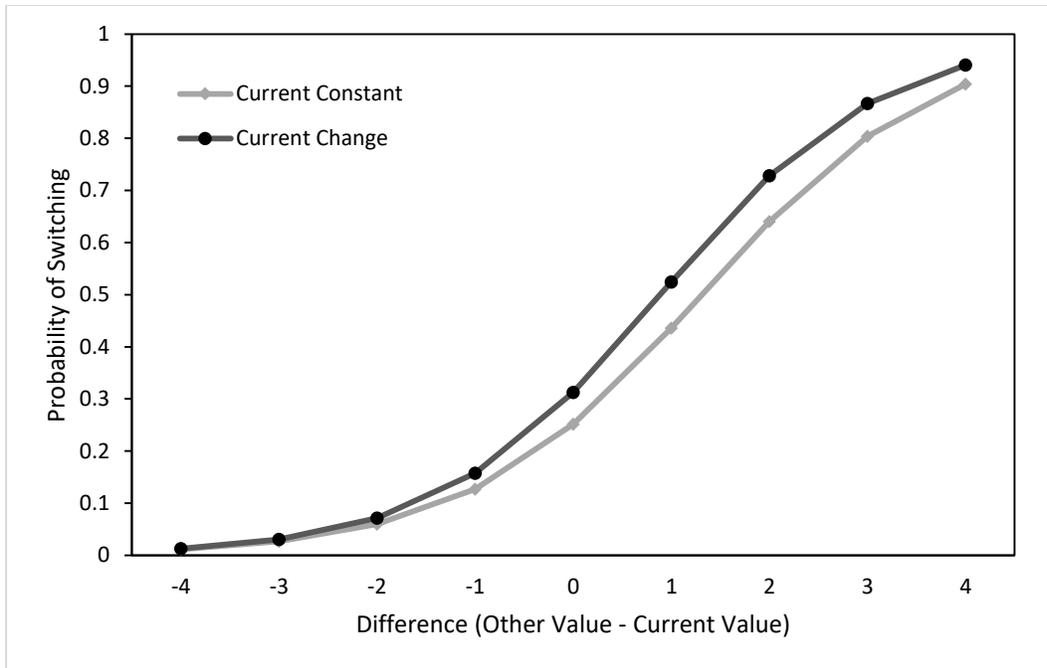


Figure 5. Probability of switching by current and difference in Experiment 1. Current constant indicates that the current task's value has remained the same from the previous trial, while current change indicates that the current task's value has decreased by a point from the previous trial. Negative differences indicate trials where the current task's value is greater than the other task's value; positive differences indicate trials where the other task's value is greater than the current task's value.

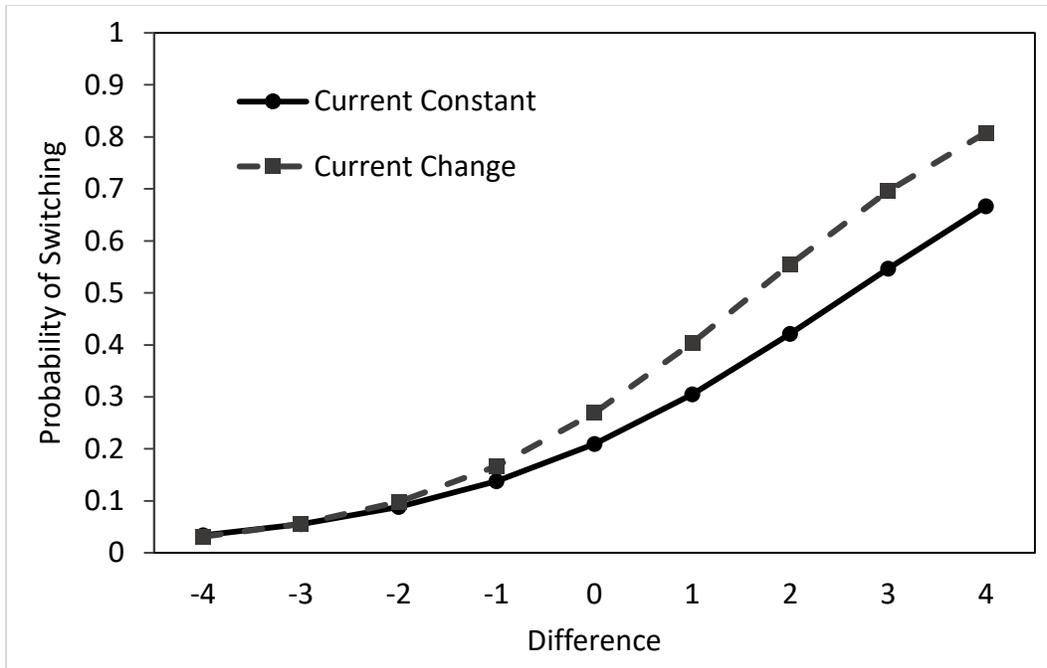


Figure 6a. Probability of switching by difference and current for high switch cost individuals in Experiment 1.

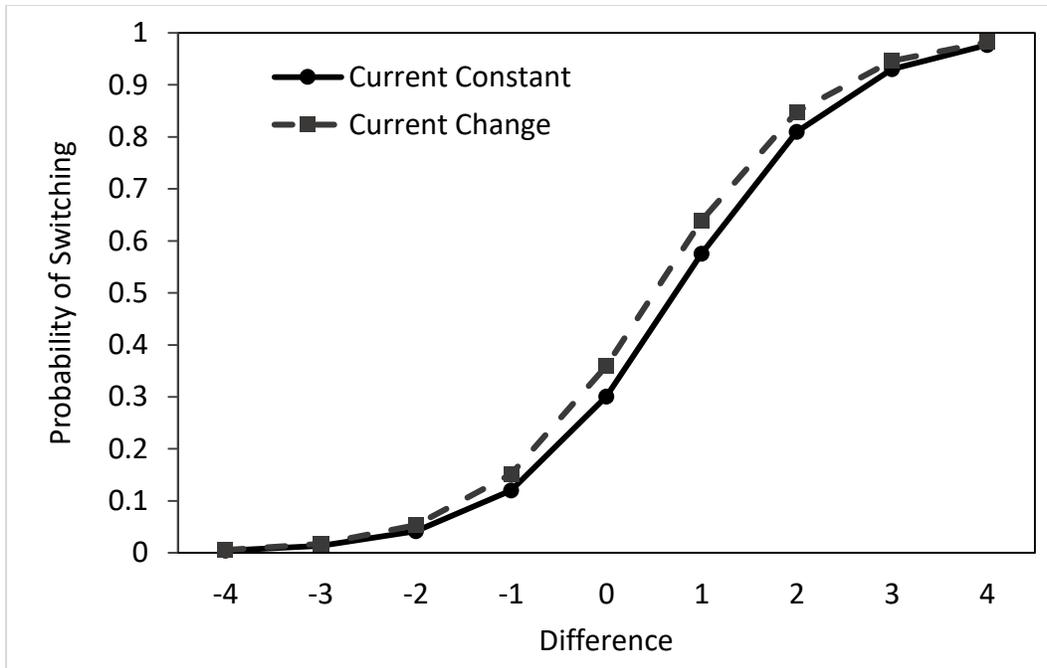


Figure 6b. Probability of switching by difference and current for low switch cost individuals.

High switch cost indicates individuals whose mean switch cost in the cued task switching procedure of Experiment 1 was one standard deviation above the mean, low switch cost indicates individuals whose average switch cost was one standard deviation below the mean. Negative differences indicate trials where the current task's value is greater than the other task's value; positive differences indicate trials where the other task's value is greater than the current task's value. Current change means the value of the current task has decreased by one point from the last trial. Current constant indicates that the value has remained constant from the previous trial.

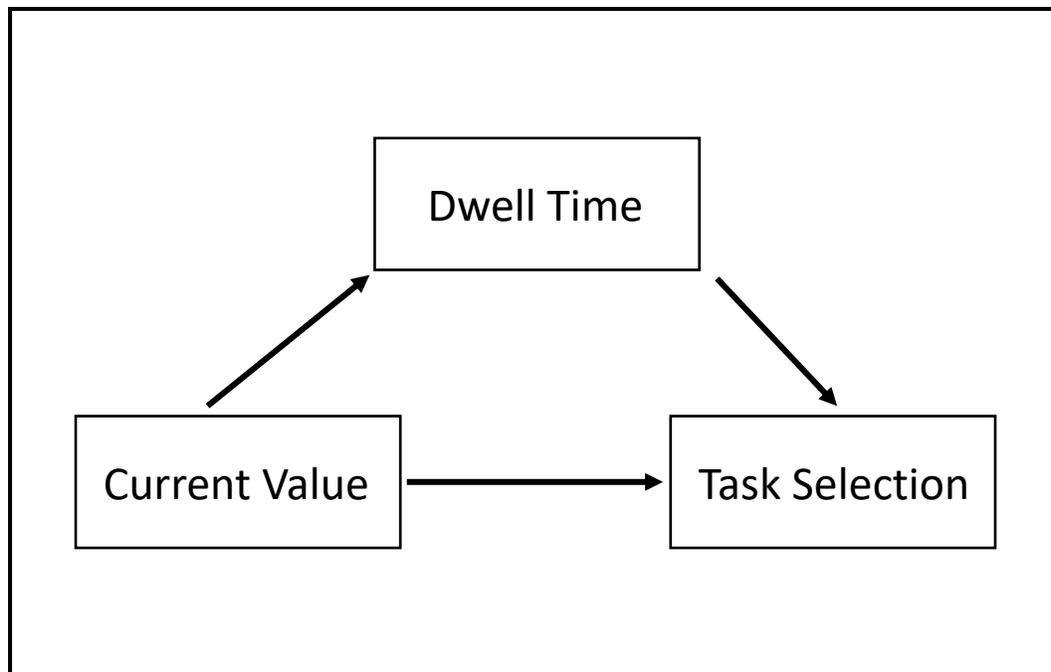


Figure 7. Experiment 2 mediation model. This models the impact of changes in the current task's value on task selection through shifts in dwell time between the current and other task's values.

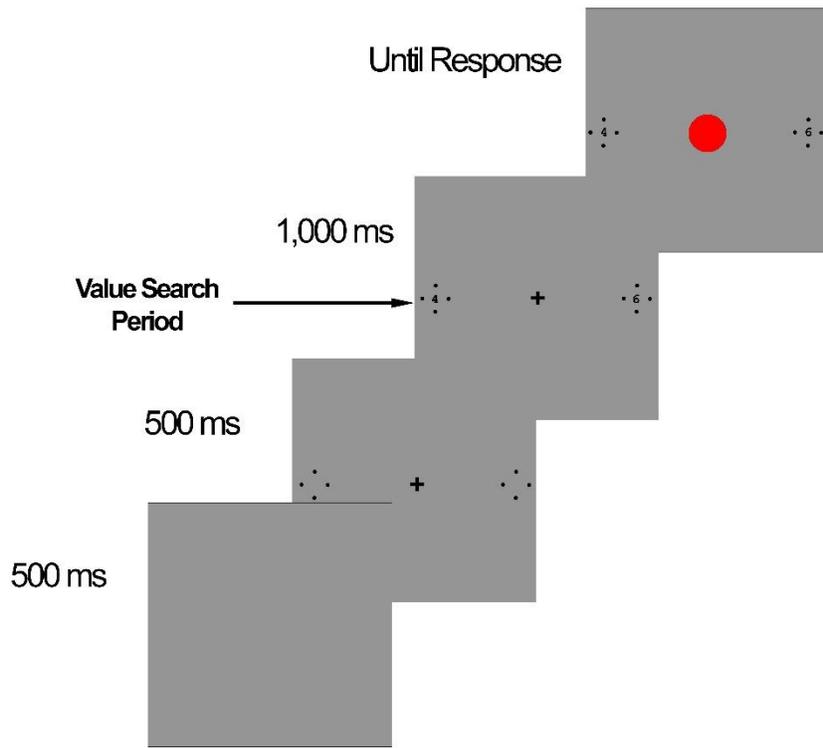


Figure 8. Experiment 2 trial sequence.

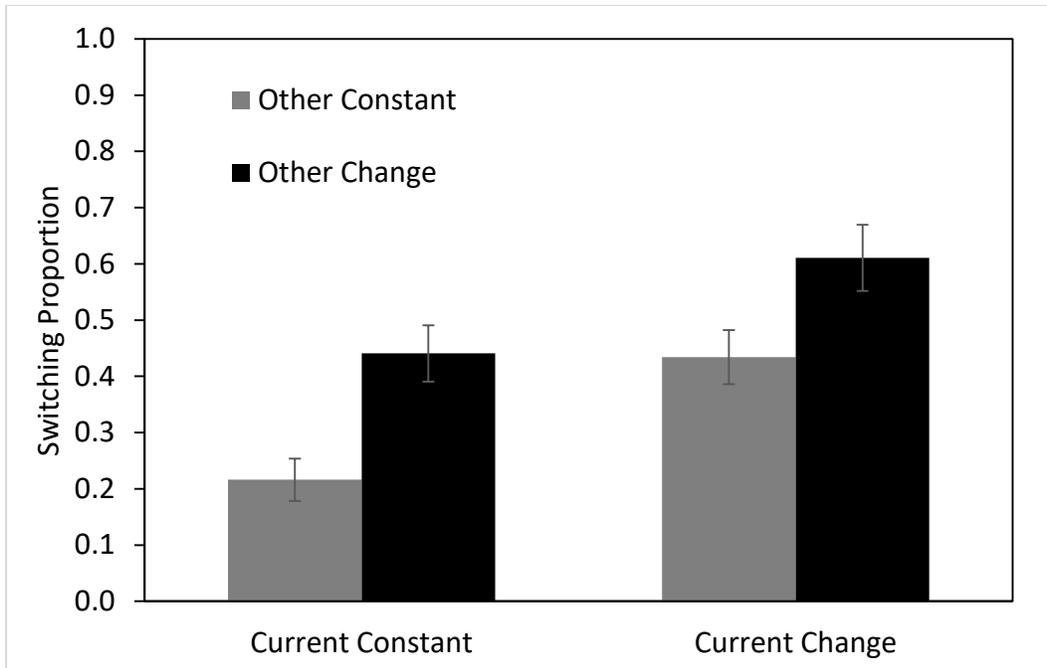


Figure 9. Mean switching proportion by reward condition in Experiment 2. Constant indicates that the point value has remained the same from the previous trial. Other change indicates that the other task's value has increased by a point from the previous trial, while current change indicates that the current task's value has decreased by a point from the previous trial. Error bars reflect standard errors.

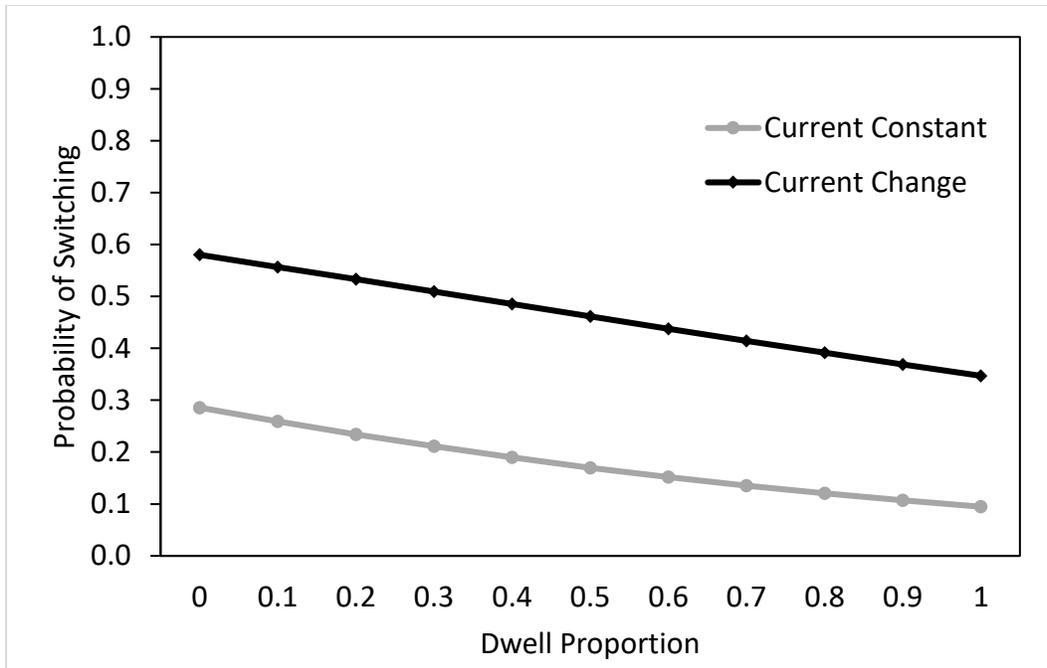


Figure 10. Probability of switching by dwell proportion in Experiment 2. Higher dwell proportions indicate a greater proportion of the trial spent dwelling on the current task's value. Current constant indicates that the current task's value has remained the same from the previous trial, and current change indicates that this task value has decreased by a point from the previous trial.

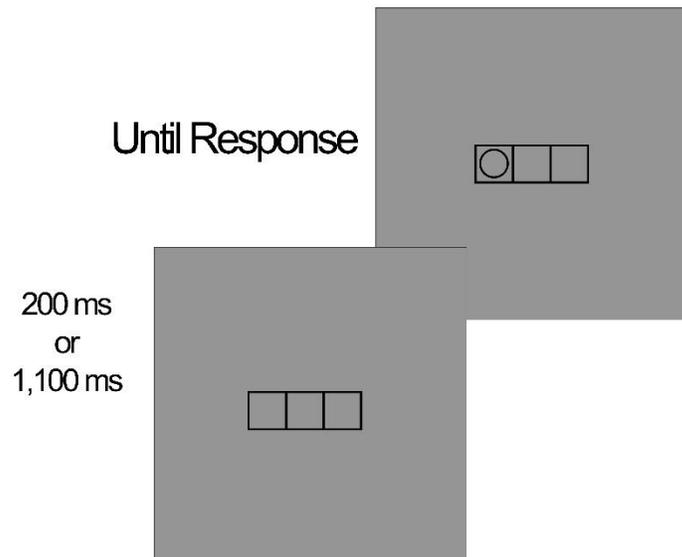


Figure 11. Experiment 3a trial sequence.

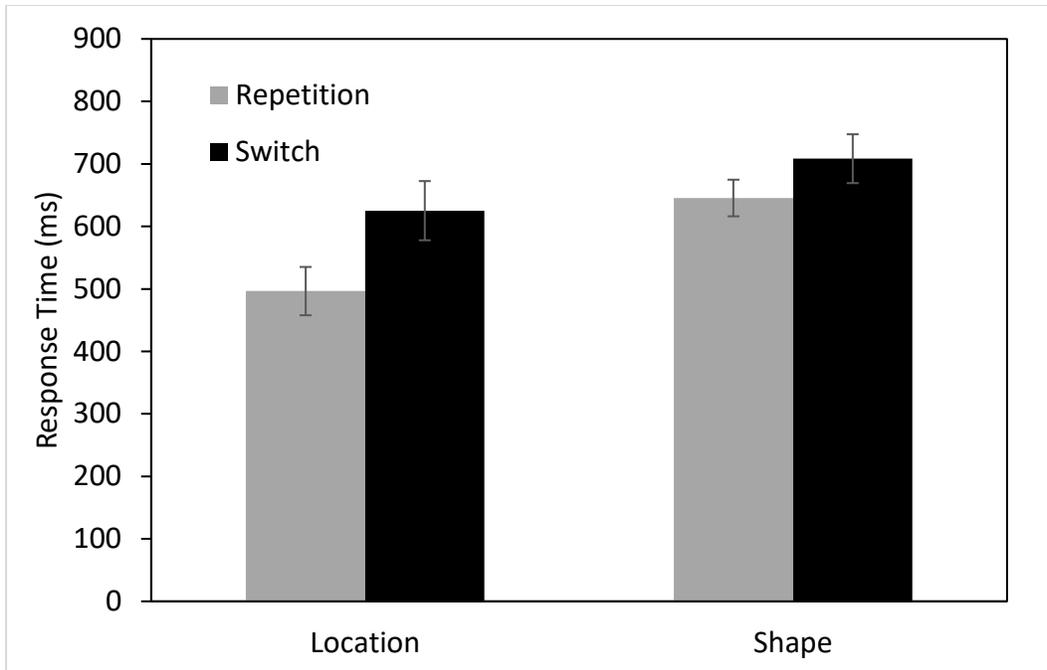


Figure 12. Mean response time by task and transition in Experiment 3a. Location is the easier task, shape is the more difficult task. Error bars reflect standard errors.

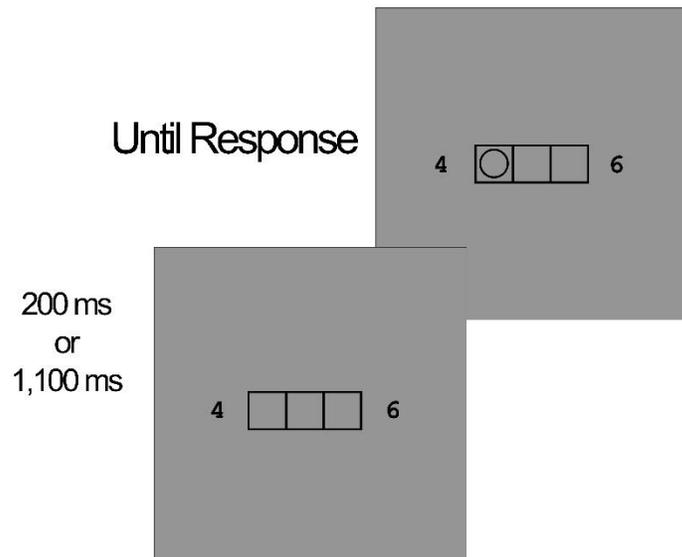


Figure 13. Experiment 3b trial sequence.

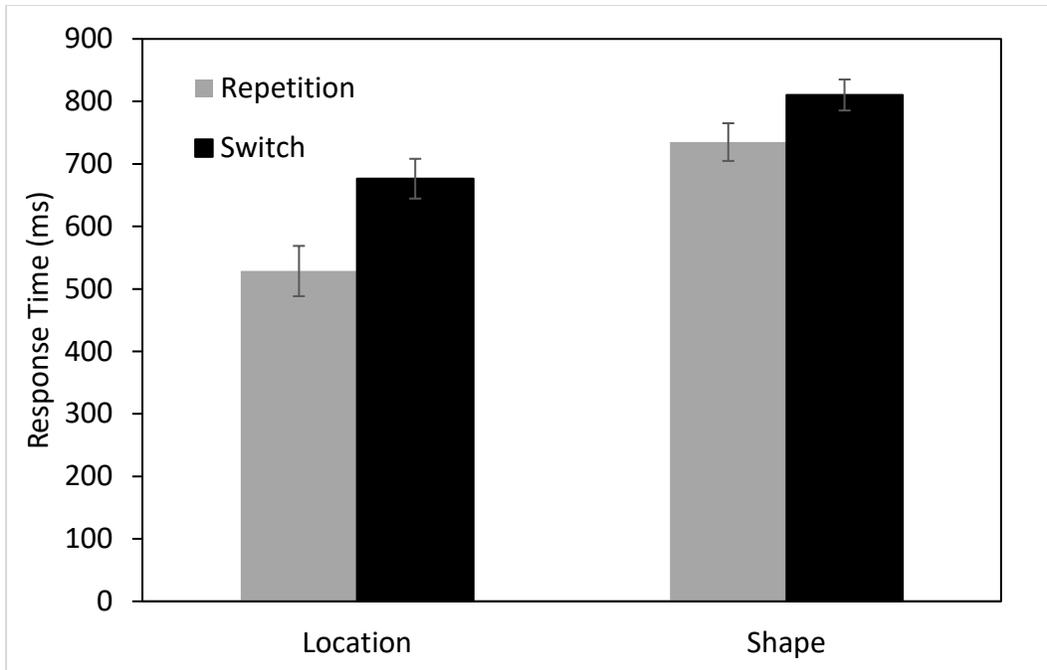


Figure 14. Mean response time by task and transition in Experiment 3b. Location is the easier task, shape is the more difficult task. Error bars reflect standard errors.

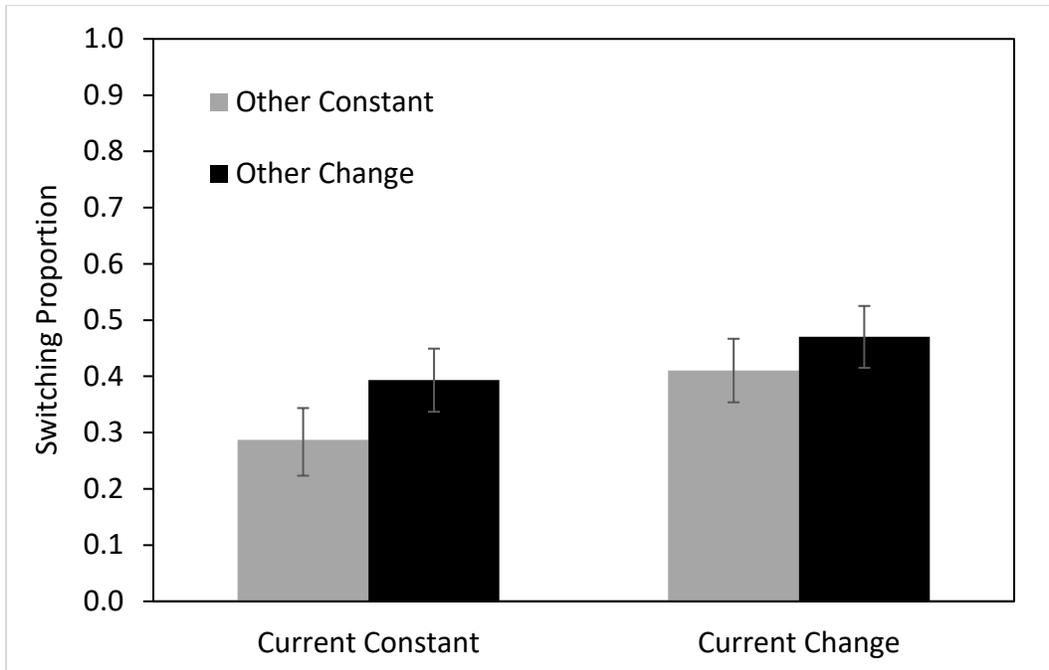


Figure 15a. Mean switching proportion by reward condition for the location task in Experiment 3b.

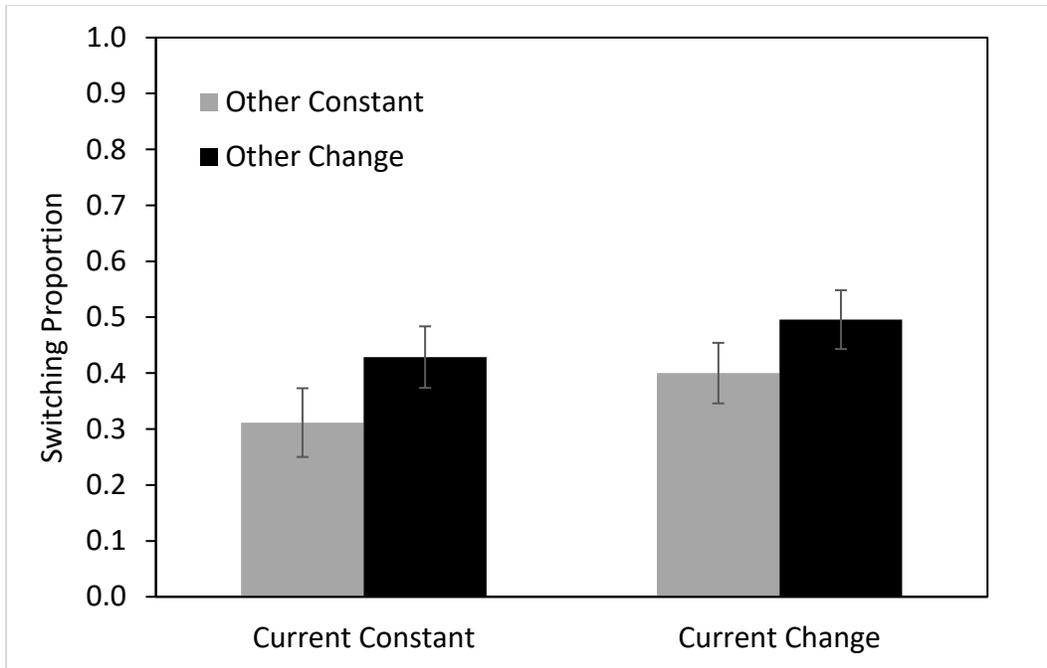


Figure 15b. Mean switching proportion by reward condition for the shape task in Experiment 3b.

The location task is the easier task, the shape task is the more difficult task. Constant indicates that the point value has remained the same from the previous trial. Other change indicates that the other task's value has increased by a point from the previous trial, while current change indicates that the current task's value has decreased by a point from the previous trial. Error bars reflect standard errors.

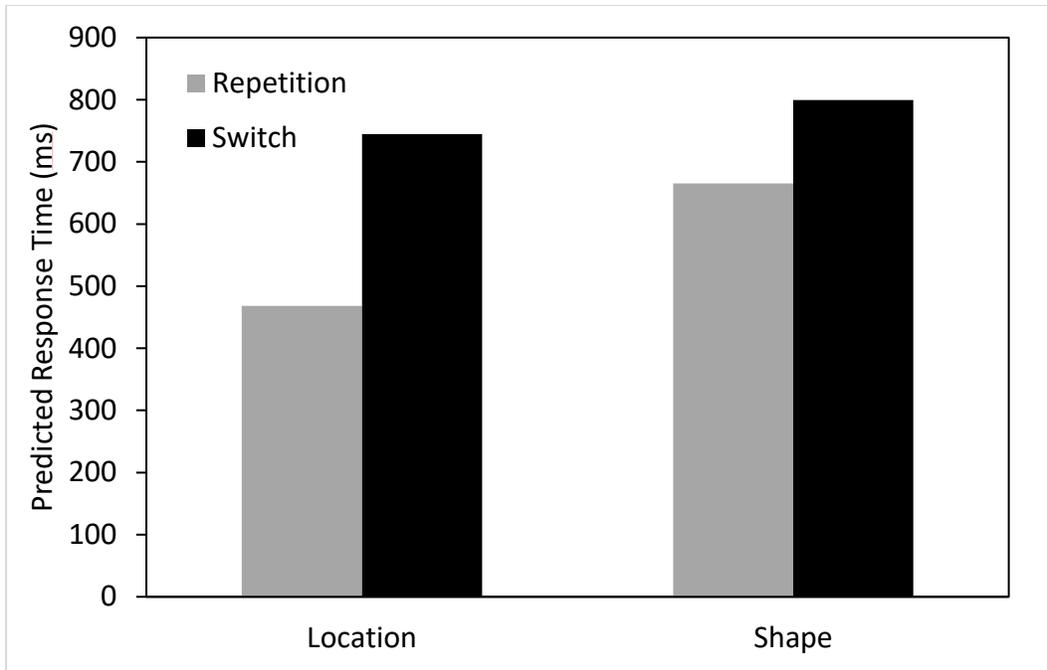


Figure 16a. Predicted response time by task and transition when the difficult task value is three points greater than the easy task value in Experiment 3b.

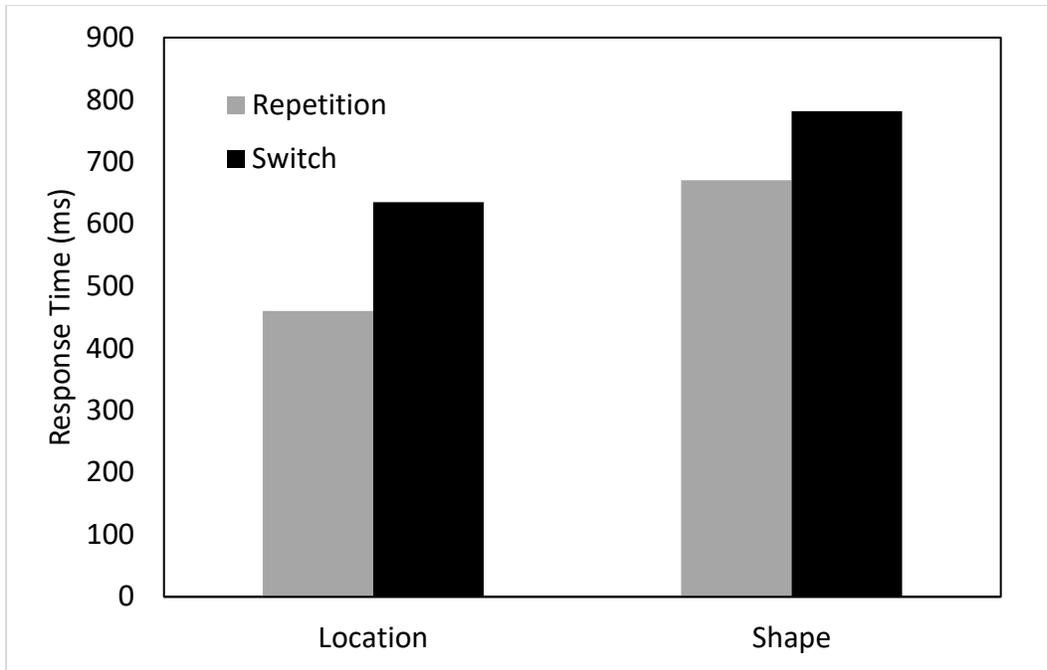


Figure 16b. Predicted response time by task and transition when the location task value is three points greater than the shape task value in Experiment 3b.

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Appendix A

Method

Participants. Sixteen participants were recruited from Lehigh University to participate in this experiment. Participants had normal or corrected-to-normal vision and color vision. No participants exceeded the 15% error rate threshold, and so all participants were retained for analysis.

Procedure. The procedure was identical to the rVTS procedure from Experiment 1 with one crucial exception – the task values did not change font color to indicate transition, but rather remained black throughout.

Results

A 2 (current: constant vs. change) X 2 (other: constant vs. change) within-participants ANOVA was conducted on the proportion of task switches. This ANOVA revealed a significant main effect of current ($F(1, 14) = 18.58, p < .001, \eta^2_p = .57$), indicating greater switching proportions after the current task's value has decreased by a point from the previous trial ($M = .35, SE = .04$) than when the current task's value has remained constant from the previous trial ($M = .23, SE = .03$). There was a significant main effect of other ($F(1, 14) = 34.30, p < .001, \eta^2_p = .71$), indicating greater switching proportions after the other task's value has increased by a point from the previous trial ($M = .37, SE = .04$) than when the other task has remained constant from the previous trial ($M = .21, SE = .03$). The interaction of current and other failed to reach significance, $F(1, 14) = 1.63, p = .22, \eta^2_p = .10$. However, planned comparisons revealed a significant difference between the Current Change and Other Change cells of the design ($F(1,$

14) = 26.29, $p < .001$, $\eta_p^2 = .65$), indicating higher switching proportions in the Other Change cell ($M = .32$, $SE = .04$) than in the Current Change cell ($M = .27$, $SE = .03$).

Appendix B

Results

To investigate the influence of task values and task difficulty on task performance, RTs were regressed on task, transition, difference, and all two- and three-way interactions of these variables. This analysis revealed a significant main effect of task ($p < .001$), such that performing the difficult task was associated with a 204 ms increase in RTs as opposed to performing the easy task. There was a main effect of transition ($p < .001$), such that switching tasks was associated with a 266 ms increase in RTs as opposed to repeating tasks. There was a significant interaction of task and transition ($\beta = -103.39, p < .001$) suggesting that, while switching to the easy task was associated with a 226 ms increase in RTs over repeating the easy task, switching to the difficult task was only associated with a 123 ms increase in RTs. Further, there was a significant interaction of transition and difference ($\beta = 16.88, p < .001$), suggesting that increases in the difference were associated with larger switch costs.

Finally, there was a three-way interaction between task, transition, and difference ($\beta = -13.06, p = .01$). Reverse coding task revealed that the two-way interaction of transition and difference was only significant for location (reported above), for task ($p = .31$). This suggests that the switch cost was only affected by the difference for the location task and not the shape task. Further, the interaction of task and transition was significant at both high ($\beta = -142.56, p < .001$) and low ($\beta = -64.22, p < .001$) levels of the difference – although, this interaction was more pronounced at high levels of the difference. This suggests that, as the easier task increased in value over the difficult task, the switch costs between the two tasks became more symmetrical, although the switch cost for the easy task was still larger. The large switch cost for the easy task became more pronounced as the difficult task increases in value over the easy task.

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EDUCATION

Ph.D., Cognitive Psychology: Lehigh University, Bethlehem, PA

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PUBLICATIONS

Fleck, J. I., Braun, D. A. (2015). The impact of eye movements on a verbal creativity task. *Journal of Cognitive Psychology*, 27, 866-881.

PRESENTATIONS AT SCHOLARLY MEETINGS

Braun, D., Arrington, C. M. (2016, November). The value of knowing when to switch: Investigating the interaction of value and control. Poster presented at the annual meeting of the Psychonomic Society, Boston, MA.

Braun, D., Weaver, S., Arrington, C. M., Reiman, K., & Wylie, G. (2016, March). Sequence complexity and context: The role of expectation in planning and execution of task sequences. Poster presented at the annual meeting of the Cognitive Neuroscience Society, New York, NY.

Braun, D. A., & Arrington, C. M. (2015, November). Raising the value of task switching: Task selection and performance under variable reward structures during voluntary task switching. Poster presented at the annual meeting of the Psychonomic Society, Chicago, IL.

Reiman, K. M., Braun, D. A., & Arrington, C. M. (2015, March). Choosing to look or looking to choose: Eye tracking in voluntary task switching. Poster presented at the inaugural International Convention of Psychological Science, Amsterdam, The Netherlands.

Braun, D. A., Arrington, C. M. (2015, March). Strategic switching: Reward structure influences selection in a dynamic decision making environment. Oral presentation at the annual meeting of the Eastern Psychological Association, Philadelphia, PA.

Braun, D. A., Fleck, J. I., Moench, E., & Ford, J. (2013) The effect of bilateral and unilateral eye-movements on creative thought. Poster presented at the annual convention of the Association for Psychological Science, Washington DC.

COLLOQUIA PRESENTATIONS

Braun, D.A. (2016, Fall). The value of knowing when to switch: The influence of cognitive control on goal-driven behavior. Presentation to Psychology Department Brown Bag Colloquium, Lehigh University.

Braun, D.A. (2016, Spring). Should I stay or should I go: Investigating the task specific nature of reward sensitivity when making task selections. Presentation to Psychology Department Brown Bag Colloquium, Lehigh University.

Braun, D.A. (2015, Fall). The neural effort engaged during encoding of planned action sequences: An fMRI investigation. Presentation to Cognition and Language Meeting Group, Lehigh University.

Braun, D. A. (2015). Strategic switching: Reward structure influences selection in a dynamic decision making environment. Presentation to Psychology Department Brown Bag Colloquium, Lehigh University.

Braun, D. A. (2014, Spring). Eye Movements and Creativity. Presentation to Cognition and Language Meeting Group, Lehigh University.

RESEARCH EXPERIENCE

Master's Thesis: How do people balance pursuing rewards while avoiding cognitive effort in multitask environments?

First Year Project: Can people use task rewards to flexibly adjust selection in a reward based voluntary task switching environment?

Undergraduate Project: The impact of eye movements on a verbal creativity task. Do bilateral eye movements lead to higher levels of creativity?

Research Assistant

Montclair State University – Cerebral Lateralization Laboratory *Fall 2013*

Configured EEG, EMG, and fNIR Biopac Hardware

Richard Stockton College of New Jersey – Memory for Words *Spring 2013*

Analyzing the effect of testing for word associations.

TEACHING EXPERIENCE

Teaching Assistant Human Neuroscience *Fall 2016*

Teaching Assistant Experimental Methods and Lab *Spring 2016*

Teaching Assistant Cognitive Psychology *Fall 2015*
Developed curriculum and administered lab-based instruction for recitation

Teaching Assistant Statistical Analysis of Behavioral Data *Spring 2015*
Instructor for weekly laboratory session
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Teaching Assistant Introduction to Psychology *Fall 2014*

PROFESSIONAL SERVICE

Ad Hoc Reviewer, *PLOS ONE* *Spring 2016*

EPA Annual Conference Submission Reviewer – Cognitive Area *Fall 2015*

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