# THE MANIFOLD ROLE OF REWARD VALUE ON VISUAL ATTENTION

by

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CERTIFICATE OF APPROVAL

PH.D. THESIS

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To my great-grandfather,
Irving *Speed* Wallace

“So we shall let the reader answer this question for himself: Who is the happier man, he who has braved the storm of life and lived, or he who has stayed securely on shore and merely existed?”

-Hunter S. Thompson
*Security*, 1955

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# ABSTRACT

Visual attention selects stimuli for further cognitive processing. Rewards powerfully influence this selection process. For instance, value-driven attentional capture demonstrates how feature-specific reward associations can result in counterproductive behavior. That effect notwithstanding, it is unclear how the nature of rewards (e.g., primary vs. secondary reinforcement, reward magnitude vs. reward probability, low-level vs. high-level reward priming) interacts with various attentional selection and control processes. In this document, I draw from reinforcement learning framework that incorporates well-studied aspects of Pavlovian and operant conditioning. This framework is tested under various conditions.

In Chapter 3, I examine how secondary reinforcers (e.g., images of U.S. dollar bills) can be used in lieu of actual monetary payment to produce value-driven attentional capture. Remarkably, I found that the mere exposure of stimulus-reward contingencies is sufficient to produce reliable levels of value-driven attentional capture. In follow-up experiments, I demonstrated that this effect generalizes to images of Monopoly money and is not due to nominal value alone. The results of Chapter 3 have implications for industrial applications such as the growing field of gamification – whereby otherwise mundane computer-based tasks are gamified by implementing micro-rewards to increase employee engagement.

In Chapter 4, I address the economic behavior of the attentional homunculus. I outline two competing hypotheses – the attentional homunculus as a rational bean counter versus an irrational fuzzy mathematician. In a series of experiments, I falsified the rational homunculus account by demonstrating how attentional behavior violates the independence axiom assumed by expected utility theory. Chapter 4 provides converging evidence that value-driven attentional capture is primarily Pavlovian and that rewards processed in vision are subject to non-linear reward

probability distortions which are characteristic of prospect theory. This finding implies that there is a parallelism between the irrational cognitive biases present in high-level economic decision-making and attentional selection.

Then in Chapter 5, I explore how higher-level attentional set behavior can be shaped by rewards. During training, participants learned to value one of two attentional sets (e.g., singleton-detection mode or feature search mode) by rewarding on the basis of search strategy. Compared to an unrewarded control group, I observed a two-fold effect of rewards. Whereas, participants highly rewarded for performing feature-search were less captured in a subsequent testing phase, participants highly rewarded for performing singleton-detection mode were more captured. The results of Chapter 5 demonstrate that attentional set behavior is amenable to implicit reward shaping. This finding provides the basis for a more comprehensive framework when it comes to examining rewarded attention effects.

Finally, in Chapter 6, I outline a general model for the manifold effects of reward on attention. This framework approaches the top-down, bottom-up debate orthogonally by addressing how rewards act on representation maps along the processing stream. This model offers testable predictions concerning population-based differences in reward processing. Lastly, I discuss the implications of this work in the context of the growing digital economy by exploring how novel value systems, such as the digital currency Bitcoin, could eventually become psychologically relevant. As a package, these results support a growing body of literature that suggests rewards have a strong influence over attentional behavior. Moreover, I show how we can use the now classic literature on reinforcement learning to better characterize the manifold action of rewards as they subtly impinge on attention to produce complex behavior.

# PUBLIC ABSTRACT

The environment is abundant with visual information. Each moment, this information competes for representation in the brain. From billboards and pop-up ads to smart phones and flat screens, in modern society our attention is constantly drawn from one salient object to the next. Learning how to focus on the objects that are most important for the current task is a major developmental hurdle. Fortunately, rewards help us to learn what is important by providing feedback signals to the brain. Sometimes, in adolescence for example, reward seeking can become the pre-potent response. This can ultimately lead to risky and impulsive behaviors that have devastating consequences. Until recently, little has been known about how rewards operate to influence the focus of attention.

In this document, I first demonstrate the robustness of various behavioral paradigms designed to measure reward processing in vision. I found that even mundane rewards, such as images of money, are effective enough to prime the attentional system on the basis of value. Remarkably, this effect extended to images of Monopoly money. This observation suggests that whole classes of visual stimuli, such as food, pornography, commercial logos, corporate brands, or money, each with its own reward salience value, are likely vying for representation in the brain. This work has implications for the growing digital economy as it suggests that novel value systems, such as the digital currency Bitcoin, could eventually become as psychologically relevant as physical currency provided sufficient use and exposure. Likewise, this work has implications for gamification in the industrial setting.

Next, I examined the sensitivity of the system to make optimal economic decisions. When faced with an economic choice normative theories of decision-making suggest that the economic actor will choose the response that affords the greatest expected utility. Contrary to this account, I developed a new behavioral paradigm (reward contingent capture) and reveal that the attentional homunculus is a fuzzy mathematician. Specifically, I found that low-level attentional processes conform to the same probability distortions observed in prospect theory. This finding supports a unified value learning mechanism across several domains of cognition and converges with evidence from monkey models.

Then, I demonstrate the influence of rewards on high-order search parameters. I found that images of money can implicitly encourage observers to preferentially adopt one of two search strategies – one that values salience versus one that values goals. Together, my results expose two distinct ways in which the very same rewards can affect attentional behavior – by tuning the salience of specific features and by shaping global search mode settings.

Lastly, I draw from my empirical results to present a unified model of the manifold role of rewards on visual attention. This model makes clear predictions for clinical applications of rewarded attention paradigms because it incorporates a dimension of complexity upon which learning processes can operate on attention. Thus, future work should acknowledge how individual traits such as developmental trajectory, impulsivity, and risk-seeking factors differentially interact with low- and high-level attentional processes.

In sum, this document puts forward the notion that rewards serve a compelling role in visual awareness. The key point however is not that rewards can have an effect on attention but that due to the nature of visual processing, reward signals are likely always tuning attention. In this way we can consider reward salience an attentional currency. This means then that deciding where to attend is a matter of gains and losses.

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# 1 BACKGROUND

## INTRODUCTION TO VISUAL ATTENTION

The human visual system is challenged with a difficult task. Each moment the retina is bombarded with visual energy. These energy signals represent a scenery of objects that may be more or less important to survival. The brain is inherently capacity limited and thus cannot veridically represent all available stimuli at a given moment. Visual attention is responsible for parsing this information. To accomplish this, attention prioritizes stimuli at the expense of others (Desimone & Duncan, 1995; Reynolds, Chelazzi, & Desimone, 1999). Consequently, stimuli compete for representation in the brain.

Survival depends on our ability to maximize rewards. Because reward outcomes fluctuate in concert with our dynamic environment, optimal decision-making processes require great vigilance. The visual system adapts to moment-by-moment environmental changes by tracking stimulus salience, current objectives, and reward (Awh, Belopolsky, & Theeuwes, 2012). To do so, visual attention itself must be continuously updated to meet the processing demands of a given scene (e.g., Lien, Ruthruff, & Johnston, 2010). Sequential trial effects demonstrate the flexibility of this process (Theeuwes, Kramer, & Belopolsky, 2004). Under optimal conditions, attention allows us to isolate those stimuli that are currently of behavioral interest from those stimuli that are irrelevant (Lavie & Tsal, 1994; Roper, Cosman, & Vecera, 2013). However, it remains unclear to what extent we control the attentional selection of specific stimuli (Awh et al., 2012).

## 1.1 BIASED COMPETITION MODEL

The biased competition theory of attention was developed, in part, to address the homunculus conundrum. Desimone and Duncan (1995) proposed when stimuli compete for attentional resources, it often is not a fair fight. That is, certain aspects of stimuli are weighted to reflect their current behavioral relevance. The system, before processing visual stimuli, is biased to allow certain stimuli access to awareness which ultimately determines which stimuli will impact behavior (see Theeuwes, 2010 for a review on how top-down attention effects may be explained entirely by appealing to bottom-up influences). The biased competition model can thus explain how attention comes to be controlled in a top-down manner without appealing to a homunculus. In viewing attention this way, Desimone and Duncan suggest that our visual system is emergent in the sense that relatively simple interactions work together to create a product that is greater than the sum of its parts.

The selectivity of the biased competition model can best be exemplified in terms of a visual search task. Duncan and Humphreys (1989) showed that search slope – measured by the change in overall response time (RT) as a function of display size – is smallest for pop-out targets and gradually increases as the distractors begin to look more like the target.

The biased competition account incorporates two general principles to explain the behavioral differences that are observed between the pop-out and serial search tasks. The first principle is that stimuli compete for attentional resources. Second, this competition is biased toward some features and stimuli over others (Vecera & Behrmann, 2001). The biased competition model suggests that when attention is used to conduct a visual search in which there is a pop-target, it is primarily dominated by strong stimulus-driven influences that direct it towards novelty or saliency. However, these stimulus-driven influences are not nearly as helpful when performing a visual search of a display where the targets and non-target have a great deal of feature overlap. To explain how difficult searches are successfully conducted, Desimone and Duncan (1995) introduce the concept of the “target template” which is essentially a description of the features of the target ("black and vertical"). They suggest that the template may be regarded as an aspect of working memory that serves to guide attention to relevant features – such as a specific color, shape, or location – and weight incoming bottom-up information that matches the template. Ultimately this weighting process biases attention to one spatial location over another.

Some visual searches are more difficult to perform than others. For example, easy searches result in shorter RT because the target is the only stimulus that matches the target template. Difficult searches include non-target distractors that partially overlap in visual features with the target. Due to the added inter-stimulus competition, difficult searches typically result in longer RT. According to the biased competition model this increased latency arises from the need to resolve stimulus competition before spatial attention can be directed toward the target location.

## 1.2 CHARACTERISTICS OF VISUAL ATTENTION

### 1.2.1 Goal-Directed Selection Criteria

The visual system parses incoming information to identify those stimuli that are relevant from those that are irrelevant to meet current goals. Goal-states guide attention only to those stimuli that in some way share characteristics of the present desiderata. When observing *goal-directed* attention we witness attentional capture that is contingent upon the features of the upcoming target. For example, after an initial search for ketchup in the refrigerator, one might unintentionally reach out for a red can of soda because of the can's color similarity to ketchup. Likewise, objects in the refrigerator that do not resemble ketchup bottles will not produce approach behavior in this aforementioned scenario. This phenomenon is known as contingent attentional capture (Folk, Remington, & Johnston, 2015).

### 1.2.2 Stimulus-Driven Selection Criteria

In contrast to goal-directed criteria, *stimulus-driven* factors are thought to guide attention to those stimuli that are most salient irrespective of their current goal relevance such as when light glints off a colleague's watch face and attracts attention away from his presentation (Theeuwes, 1992). Transient stimulus events such as the abrupt onset or offset of an object have been shown to enhance stimulus priority (Jonides & Yantis, 1988).

### 1.2.3 General Selection History Factors

Stimulus-driven and goal-driven factors provide a useful dichotomy to conceptualize the ostensibly separable influences of attentional selection, but they leave a large explanatory gap (Awh et al., 2012). Although some factors known to influence attentional selection can be neatly packed as purely stimulus-driven and purely goal-driven, other factors such as priming (Maljkovic & Nakayama, 1994), reward history (Della Libera & Chelazzi, 2006), and target context (Chun & Jiang, 1998) have all been shown to affect selection but these effects do not necessarily rely on goals or particular stimulus attributes (Le Pelley, Pearson, Griffiths, & Beesley, 2015; Pearson, Donkin, Tran, Most, & Le Pelley, 2015). Therefore, stimulus-driven and goal-driven attentional factors do not comprehensively account for extant data.

## 1.3 EXTANT THEORETICAL DEBATE

### 1.3.1 Top-Down vs. Bottom-Up: A False Dichotomy

A recent attentional selection incorporates stimulus representation maps that independently code for goals, salience, and selection history (see **Figure 1.1**). Signals from the lesser maps combine to produce an integrated attentional priority map. Integrated priority maps such as these (Itti & Koch, 2001) have a cortical locus and have been traced to the lateral inter-parietal sulcus (Bisley & Goldberg, 2010). **Figure 1.1** depicts subordinate signal maps that feed into a master

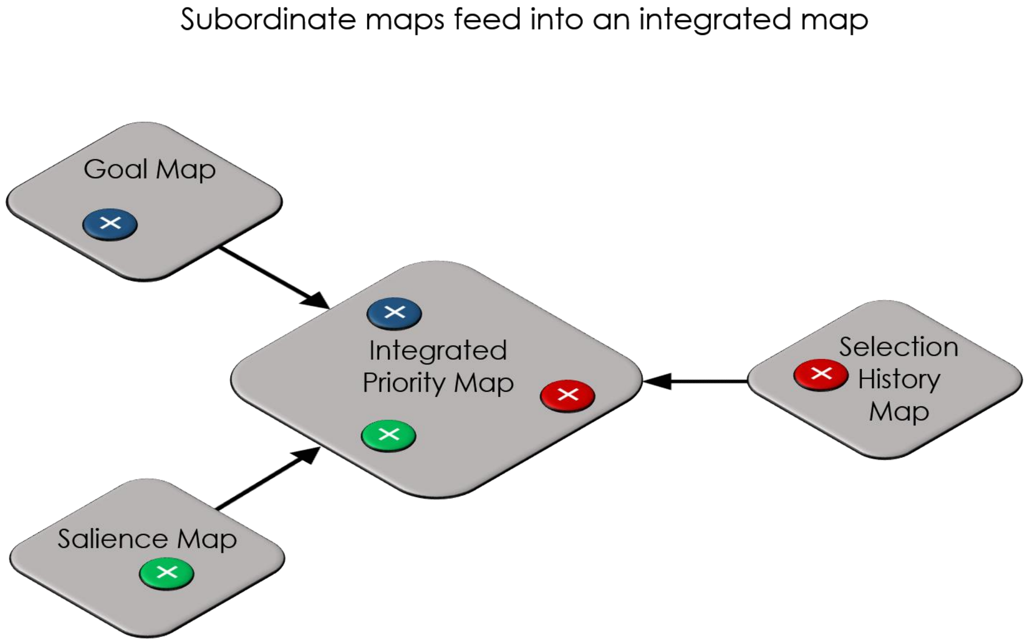

**Figure 1.1** *Activation maps.* Illustration of three individual maps as they activate an integrated priority map. The selection history map is hypothesized to be unique from the goal map and the salience map. Value-driven attentional processes are thought to occur in the selection history layer. Adapted from Awh et al. (2012)

priority map (adapted from Awh et al., 2012). Awh and colleagues (2012) proposed these maps integrate signals from several sources. Each map codes for a distinct factor. At least three subordinate maps are known to contribute to the master priority map. There is a goal map, a salience map, and a selection history map. Rewards rely on selection history and produce *value-driven attentional selection*. Thus, according to this model, value-driven attentional selection is distinct from goal-directed and stimulus-driven selection.

### 1.3.2 Evidence for a Unified Value-Driven Selection Mechanism

Learned stimulus-reward associations are extraordinarily influential in guiding behavior (Pavlov, 1927). Optimal attentional deployment helps maximize rewards and minimize losses (see Anderson, 2013 for a recent review). A number of studies have demonstrated that rewards can enhance attention to task relevant stimulus features (Anderson, Laurent, & Yantis, 2011; Della

Libera & Chelazzi, 2006). Rewards can enhance selective attention by modulating activity in visual cortices (Hickey, Chelazzi, & Theeuwes, 2010; Serences, 2008). These value-driven attention effects demonstrate the tight linkage between environmental cues and behavior. Further, they suggest that the attentional system can learn to adapt to a dynamic environment (for a review on attentional control, see Vecera, Cosman, Vatterott, & Roper, 2014). Learned stimulus-reward associations also enhance our ability to quickly identify and discriminate stimuli (Della Libera & Chelazzi, 2009). Those effects notwithstanding, it is unclear if rewards act independently from goals and salience, as implied in the model in **Figure 1.1**. Although Awh et al. (2012) proposed that rewards indirectly feed into the integrated priority map via the selection history map, Stănişor et al. (2013) proposed a unified account of reward processing in vision. In contrast to an independent components model, the unified model does not rigorously distinguish reward-processing from top-down selection mechanisms. Instead, Stănişor et al. (2013) posit that rewards and top-down attention share overlapping, if not the same, cortical substrate in early vision (V1). Therefore, one possibility is that rewards could act on each subordinate map independently. Alternatively, rewards may operate uniformly across all maps. In **Chapters 3-5**, I describe novel datasets that were collected as a means to probe the attentional system at its various loci to begin to isolate the many roles that rewards could potentially serve. Specifically, **Chapter 3** addresses the role of secondary reinforcers in the canonical value-driven attentional capture task. **Chapter 4** extends these feature-based reward effects to a novel task (reward contingent capture) and explores whether the attentional homunculus obeys critical axioms assumed by expected utility theory. **Chapter 5** contributes to the extant theoretical debate on attentional selection by providing new evidence in favor of a unified theory of reward-processing and top-down selection. Lastly, in

**Chapter 6**, I draw from the empirical results obtained in **Chapters 3-5** to present a model that describes the manifold role of reward processing in attentional selection.

# 2 THE TREATMENT OF VALUE IN THE BRAIN AND ITS IMPACT ON BEHAVIOR

## 2.1 NEURAL MARKERS OF VALUE PROCESSING

### 2.1.1 Anatomical Structures

There are many anatomical structures that have been associated with reward processing. They include the nucleus accumbens (Knutson, Adams, Fong, & Hommer, 2001), the anterior and posterior cingulate cortex (Poremba & Gabriel, 1997, 1999), substantia nigra, and the locus coeruleus (Bouret & Sara, 2004) among others. These areas work in concert to produce reward effects throughout the brain. The end result is that rewards and reward representations are powerful in helping organisms learn about the environment.

### 2.1.2 Neural Networks

Visual attention areas share mutual connectivity with reward areas (Serences, 2008). This architecture incorporates feedback loops where attentional filtering processes are modified by endogenous reward signals (Stănişor, van der Togt, Pennartz, & Roelfsema, 2013). Learned cues evoke dopaminergic responses that are indistinguishable from primitive rewards such as food and water (Bromberg-Martin & Hikosaka, 2011; Lauwereyns, Watanabe, Coe, & Hikosaka, 2002). For this reason, some cues are often sought and by virtue produce ‘wanting’ behaviors. Such a cue is said to have incentive salience – a term that reflects the motivational and perceptual properties of a cue (Berridge & Robinson, 1998; Robinson & Berridge, 2008).

### 2.1.3 Electrophysiology

Electrophysiological studies on reward demonstrate robust processing of feedback specific information (Krebs, Boehler, & Woldorff, 2010). Specific forms of these feedback signals (e.g., feedback related negativity, error-related negativity) have been observed in gambling tasks (Yeung, Holroyd, & Cohen, 2005).

### 2.1.4 Hebbian Plasticity

The repeated activation of the above substrates and pathways helps produce learning (Rescorla & Wagner, 1972). This process is thought to occur via Hebbian learning whereby neuronal activation serves to potentiate subsequent activation via a self-reinforcing feedback process (Hebb, 2005).

## 2.2 BEHAVIORAL ASSAYS OF VALUE PROCESSING

### 2.2.1 Motivated Behavior

Animal behavior is naturally motivated by an organism's needs and the availability of resources in the environment. When animals interact with the environment, they learn that (1) some behaviors are fruitful, and (2) some stimuli come to predict reward. Therefore, there is a distinction between response-reward (operant) and stimulus-reward (Pavlovian) mappings. This distinction is important and useful in order to describe motivated behavior.

When a behavior is closely followed by reward, it is common for that behavior's frequency to increase relative to unrewarded behaviors. This observation has become established as the *Law of Effect*. The Law of Effect characterizes how animals are motivated to obtain rewards in order to satisfy basic needs (Thorndike, 1911). Under the Law of Effect framework, the response is paired with rewards. Response-reward mappings, as described by the Law of Effect, fall under the domain of *operant conditioning* (Skinner, 1938). In contrast, *Pavlovian conditioning* characterizes motivated behavior as a function of stimulus-reward mapping. The wealth of knowledge pertaining to Pavlovian conditioning tells us that an initially neutral stimulus becomes a conditioned stimulus when it signifies the availability of reward (e.g., Hall, 2003; Mackintosh, 1975; Pavlov, 1927; Rescorla & Wagner, 1972; Rombouts, Bohte, Martinez-Trujillo, & Roelfsema, 2015).

### 2.2.2 Incentive Salience

The concept of *incentive salience* was born out of the drug addiction literature to address the high incidence of relapse in recovering drug addicts (Robinson & Berridge, 2008). During treatment, a recovering addict does not have access to drugs. At the same time, they are not exposed to drug cues (e.g., paraphernalia, drug houses, etc.). After successfully completing treatment, a recovering addict must avoid drug use to have the best chances against relapse. Early models of addiction placed emphasis on post-treatment drug abstinence as the best method of preventing relapse. It was later discovered that when a recovering addict is exposed to drug cues they often cannot resist the urge to use. Incentive salience was incorporated into addiction models to account for the strong cue-drug relationship in addition to the traditional response-drug association. Thus, incentive salience relies heavily on Pavlovian conditioning principles.

### 2.2.3 Rewarded Attention

Rewards and reward-predictive cues become salient and potentiate behavior. Reward effects have been observed in overt attention ( e.g., saccadic eye-movements, Anderson & Yantis, 2012; Hickey & van Zoest, 2012; Schroeder & Holland, 1969; Theeuwes & Belopolsky, 2012), feature-based attention (Anderson, 2013; Della Libera & Chelazzi, 2006; Della Libera & Chelazzi, 2009; Gottlieb, 2012; Hickey, Chelazzi, & Theeuwes, 2010; Krebs et al., 2010; Raymond & Brien, 2009), object-based attention (Lee & Shomstein, 2013; Shomstein & Johnson, 2013), inter-trial attentional priming (Kristjánsson, Sigurjónsdóttir, & Driver, 2010) and attentional carry-over (Hickey et al., 2010; Hickey, Chelazzi, & Theeuwes, 2011; but see Ásgeirsson & Kristjánsson, 2014).

### 2.2.4 Value-Driven Attentional Capture

The clearest reward effect in feature-based attention comes from the value-driven attentional capture (VDAC) paradigm which demonstrated attentional capture to distractors previously associated with reward (Anderson, Laurent, & Yantis, 2011). The VDAC paradigm provides an indirect method to assess motivated attention. VDAC is robust and can persist seven to nine months after initial training (Anderson & Yantis, 2013). The VDAC paradigm consists of training and testing phases. During training, participants search for a red or green target circle. These targets are correlated with either a high-value (10¢) or low-value (2¢) monetary reward, based on their color. During the testing phase, no rewards are delivered. Instead, participants search for a neutral colored square. On a portion of trials, red and green circles appear as task-irrelevant distractors. Typically, participants' response time (RT) is significantly larger when a previously rewarded distractor color is present than when it is absent. The VDAC effect is evidence that reward-predictive cues induce attentional approach behavior in the form of distraction. This, in turn, suggests that VDAC relies on Pavlovian conditioning (Le Pelley et al., 2015).

# 3 FUNNY MONEY: THE ATTENTIONAL VALUE OF OVERLEARNED SECONDARY REINFORCERS

## 3.1 MOTIVATED-TO-EARN

Monetary rewards are powerful in shaping behavior. However, the effect of money on attention can be multifaceted as it can influence attention via response-reward or stimulus-reward mappings. In addition, the receipt of monetary reward increases overall arousal. Gambling addiction serves as testament to that fact. The pathways model of gambling describes how problem gamblers often chase the adrenaline rush that accompanies wins (Blaszczynski & Nower, 2002). Although the risks are considerably less, the paid VDAC paradigm, as conducted in the laboratory, crudely resembles a video slot machine found in casinos. In both venues, actors are motivated to maximize rewards (money). Therefore, I introduce the *motivated-to-earn* hypothesis that stipulates that in order to observe VDAC, participants must always anticipate earning or otherwise obtaining the rewards at stake.

The motivation to earn hypothesis is supported by empirical evidence showing that rewards can sometimes lead to better overall task performance. For example, performance-contingent monetary rewards reduced compatibility effects in a flanker task (Hübner & Schlösser, 2010) and increased perceptual sensitivity (d') to detect faces in a spatial cuing paradigm (Engelmann, Damaraju, Padmala, & Pessoa, 2009). In these studies, rewards are thought to impel participants' to exert greater attentional effort. Because the VDAC paradigm usually incorporates monetary reward (but see Anderson, 2015), the rewarded attention effects in the VDAC paradigm are always observed when participants are motivated-to-earn rewards. This is problematic because it means that VDAC effects cannot be isolated from the motivation to earn.

Some evidence has recently emerged that contradicts the motivated-to-earn hypothesis. In a gamified VDAC study, game points without monetary rewards did not produce the VDAC effect (Miranda & Palmer, 2014). Another study failed to observe VDAC when participants were paid, but rewards were not correlated with any specific target feature (Sali, Anderson, & Yantis, 2014). Additionally, an example from animal training (described below) offers a complementary approach to address the motivated-to-earn hypothesis (Skinner, 1951).

## 3.2 SECONDARY REINFORCEMENT

Learned reward cues are valuable because they can convey predictive information about rewards in the environment. As a consequence, particularly reliable reward cues can act as rewards themselves. Such cues are known as *secondary reinforcers*. Unlike food or other basic biological needs that act as primary reinforcers, money merely symbolizes reward and must be exchanged before it may convey a benefit. Money is a secondary reinforcer and is rewarding by virtue of its association with primary reinforcers. How secondary reinforcers come to direct attention is not fully known.

In operant conditioning paradigms, primary reinforcers can be replaced by secondary reinforcers with little detriment to learning. For example in animal training, trainers often reward a desired behavior with food. The use of food is effective, but impractical because too much food can quickly lead to satiation. Satiation should be avoided because it contravenes training goals and limits the amount of training that can take place in a single session. To prevent satiation, a professional trainer can simultaneously present a neutral tone, such as a click or other tone, with food via the Pavlovian conditioning procedure. Over time, the tone acquires incentive salience, and serves as a secondary reinforcer. As long as the tone continues to periodically predict food, it will continue as an effective behavior-shaping tool (Skinner, 1951). This suggests that there are periods of time in which secondary reinforcers motivate behavior as much as primary reinforcers.

In the previous example, secondary reinforcers were helpful for the trainee because they provided predictive information that could be leveraged to eventually obtain food. Also, secondary reinforcers were helpful for the trainer as a practical operant conditioning tool that prevented satiation. We can analogize the animal training example to the VDAC paradigm by conceiving of the trainer as the computer-based task and the trainee as the participant. In animal training, the neutral tone becomes rewarding on its own. Therefore by extension, monetary images – without financial remittance – should be rewarding in the VDAC paradigm. This analogy embodies the incentive salience hypothesis. In contrast to the motivated-to-earn hypothesis, the incentive salience hypothesis would predict that a particularly powerful secondary reinforcer should produce VDAC. If secondary reinforcers are delivered on a trial-by-trial basis, but in the absence of expected payout, then high-value secondary reinforcers should nevertheless have a larger impact on attention than low-value secondary reinforcers, even in the absence of the rewards themselves. To test this prediction, I asked whether images of U.S. dollar bills, as overlearned secondary reinforcers, were rewarding enough to produce VDAC in participants who were not motivated-to-earn actual monetary gains.

## 3.3 EXPERIMENTS 1A & 1B: U.S. DOLLAR BILLS

I modified the VDAC task by incorporating high-resolution images of U.S. dollar bills ($5 and $20) in lieu of monetary reward. Participants received course credit, and this credit was not related to my reward manipulation. Most importantly, participants did not receive any monetary reward (i.e., they were not paid to participate). The procedure was similar to previous work (Anderson et al., 2011; Roper, Vecera, & Vaidya, 2014). During training, participants searched for either a green or a red target and each target was associated with a monetary value (e.g., the green target was more likely to be followed by the \$20 image than the \$5, opposite for the red target). The bill images were presented in lieu of monetary rewards and participants received no feedback regarding the accumulation of any earned value. During testing trials, participants searched for a newly defined target (i.e., a diamond shape) amongst distractors. Crucially, in some trials a distractor was presented in the same color that had been associated with money during training (i.e., red and green). These distractor present trials allowed me to test the effect of the associations learned during the training phase by means of attentional capture to previously rewarded colors. The procedure preserved the trial-by-trial characteristics needed for Pavlovian conditioning and removed the external motivation to obtain a monetary reward. Remarkably, I demonstrate that the mere sight of money, when associated with specific targets, can produce VDAC.

### 3.3.1 General Methods

#### *Participants*

Forty University of Iowa undergraduates participated for partial course credit. All had normal or corrected-to-normal vision. Twenty participants (17 female, mean age = 18.2 years, SD = .37 years, range = 18-19 years) took part in Exp. 1a and twenty participants (13 female, mean age = 19.0 years, SD = 1.23 years, range = 18-23 years) took part in Exp. 1b. Participants in both experiments completed the training and testing phases of the VDAC computer-based task. In Exp. 1b, I additionally probed participants on their explicit knowledge of the reward contingencies by administering a post-experimental questionnaire (see **APPENDIX A**).

#### *Apparatus*

An Apple Mac Mini computer displayed stimuli on a 17-in. CRT monitor and recorded keyboard responses and latencies. The experiment was controlled using MATLAB (The

MathWorks, Natick, MA) and the Psychophysics Toolbox (Brainard, 1997). Participants were seated 60 cm from the monitor.

*Distribution of trials*

The experiment commenced with a 24-trial practice block in which performance feedback was given to help the participant learn the stimulus response mappings. During practice, all stimuli were presented in white on a black background. No rewards were displayed in practice. The training phase immediately followed practice and consisted of 240 trials which were segmented

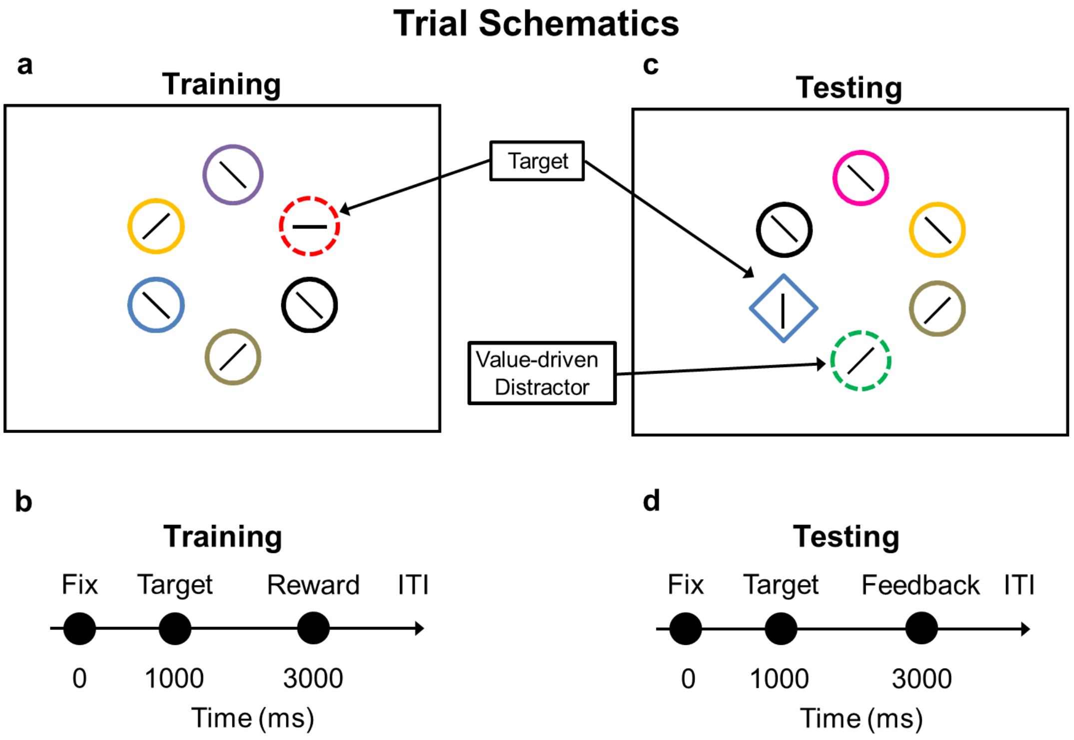

**Figure 3.1** *Trial schematics*. (a) Training array: red and green rings – denoted here by the broken line – were associated with high-value ($20) and low-value ($5) stimuli during training. (b) Timing of training trials: Fix = fixation point, ITI = inter-trial interval. (c) Testing array: targets were blue diamonds and previously rewarded distractors appeared on half of the trials. (d) Timing of testing trials: No bills were presented during the testing phase. Instead, feedback text (“Correct!” and “Wrong!”) was provided. These displays are for illustration only; in the experiment, white line segments appeared on black backgrounds (see **3.3.1 General Methods**)

into 60-trial blocks. The testing phase followed the training phase and was composed of 288 trials which were segmented into 72-trial blocks.

*Training phase*

The stimulus display consisted of six colored rings arranged in a circular array (see **Figure 3.1**). Each ring was rendered in a different color, and the task was to report the orientation of a line segment within a red (RGB value: 255, 0, 0) or green (RGB value: 0, 255, 0) target ring, one of which was present on every trial. The target ring was equally likely to be red or green and equally likely to appear at any of the six locations along the circular stimulus array. Each ring subtended a visual angle of 2˚ with a line width of 5 pixels. The total stimulus array subtended a visual angle of 10˚ and was centered within the display. Distractor colors were randomly drawn without replacement from the following pool of values: blue (RGB value: 0, 0, 255), magenta (RGB value: 255, 0, 255), white (RGB value: 255, 255, 255), tan (RGB value: 237, 199, 114), yellow (RGB value: 255, 255, 0), and cyan (RGB value: 0, 255, 255).

Each ring contained a white line segment (length = 1.2˚ visual angle; width = 0.2˚ visual angle) that was tilted either 45° or 135°. Importantly, the line inside the target ring was either vertically (0°) or horizontally (90°) aligned. Participants were instructed to report the orientation of the line within the target ring by pressing either the “z” or “?” key. The key-orientation mapping was counterbalanced.

Every trial commenced with a centrally presented fixation point that remained on screen for 1,000 ms. This was followed by the stimulus array, which was displayed for 2,000 ms or until participants responded (see **Figure 3.1b**). After an incorrect response, the text, “Wrong!” was displayed at the center of the screen in 24-point Helvetica font for 1,000 ms. After a correct response, an image of a U.S. bill ($5/$20) was centrally presented on-screen for 1,000 ms (see

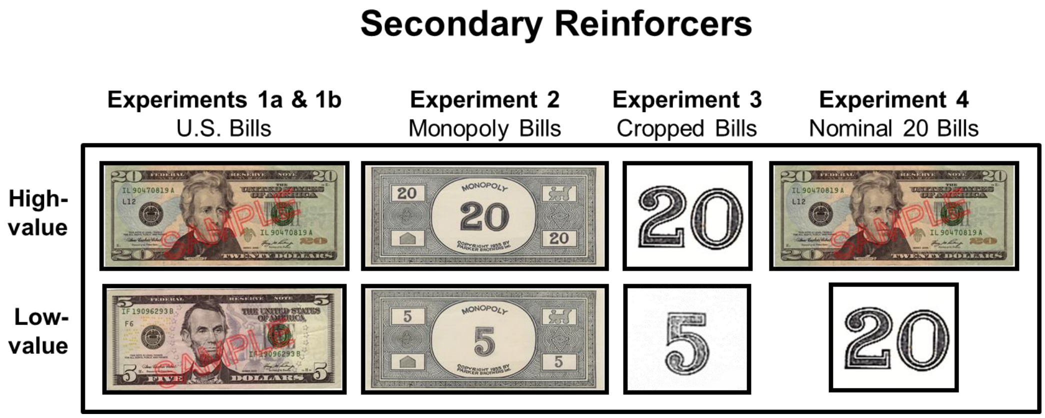

**Figure 3.2** *Secondary reinforcers.* High-resolution images of U.S. dollar bills (Exps. 1a & 1b), Monopoly money (Exp. 2), and cropped Monopoly money (Exp. 3) were presented after every correct training trial. Experiment 4 featured a between category comparison ($20 U.S. dollar bill vs. cropped Monopoly 20 bill). The word “SAMPLE” seen here written across the U.S. bills, was not present during the experiment

**Figure 3.2**). These bill images corresponded to the veridical dimensions of a physical bill (19.72˚ visual angle wide x 4.75˚ visual angle tall). Specific feedback schedules were established such that one target color was highly rewarded and the other target color was lowly rewarded. For instance, for half of the participants the high-value color was red and the low-value color was green. In this case, a correct response to a red target was followed by the presentation of a $20 bill in 80% of trials and a $5 bill in 20% of trials. In contrast, a green target was followed by a $5 bill in 80% of trials and a $20 bill in 20% of trials. These color-reward associations were counterbalanced across participants. Crucially, and in contrast to previous VDAC studies, participants knew in advance that the bill images did not reflect an actual payment of money at the current trial or at the conclusion of the experiment. The questionnaire data from Experiment 1b confirmed that at no point did participants anticipate monetary compensation (see **3.3.3 Task Questionnaire Dataset** and **APPENDIX A**).

*Testing phase*

To assess the impact of previously rewarded colors, participants completed testing trials immediately after the conclusion of training. The testing sessions were identical to the training sessions except that participants always searched for a diamond-shaped target among five colored distractor rings and reported the orientation of a line segment within the diamond. Every trial, the color of the diamond target was randomly chosen from the following pool of colors: blue, magenta, white, tan, yellow, and cyan. After participants responded, accuracy feedback (i.e., “Correct!” or “Wrong!”) was displayed for 1,000 ms (see **Figure 3.1**, panels c and d). Importantly however, no images of dollar bills were presented during the testing phase. The critical manipulation in the testing phase is the color of the distractor rings. For one-half of testing trials, the distractors’ colors were randomly drawn without replacement from the aforementioned pool of colors (i.e., reward-neutral colors). On the other half of testing trials, one of the distractors was presented either in red or in green (red in 25% and green in another 25% of testing trials), and thus in a color that was formerly rewarded during training. These previously rewarding colors were now poised to distract attention away from the diamond-shaped target.

**Table 3.1** *Training phase mean RT for Exps. 1-4.*

| | Training Phase RT | | | |
|---|---|---|---|---|
| | Low-Value Target | | High-Value Target | |
| | *M* | SEM | *M* | SEM |
| Exp. 1a | 815 | 29 | 791 | 28 |
| Exp. 1b | 769 | 33 | 760 | 30 |
| Exp. 2 | 764 | 36 | 739 | 28 |
| Exp. 3 | 727 | 21 | 719 | 19 |
| Exp. 4 | 826 | 45 | 787 | 42 |

*Post-experimental questionnaire*

At the experiment's conclusion, the 20 participants in Experiment 1b were probed on their knowledge of the task and they were asked about the strategies they used to complete the task. The questionnaire was administered via paper and pencil and consisted of nine items: six open ended questions and three 2-alternative forced choice questions. Each question was administered on a separate sheet, one-at-a-time. The questions and some representative responses are listed in **APPENDIX A**.

### 3.3.2 Results

*Training phase*

Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis. This eliminated 5.9% of the data for Exp. 1a and 6.8% for Exp. 1b. Mean correct RT for training trials were separately computed for high- and low-value reward colors (see **Table 3.1** *Training phase mean RT for Exps. 1-4.*).

*Exp. 1a*

A paired-samples $t$-test revealed shorter mean RT for high-value compared to low-value colors, $t(19) = 2.39$, $p = .006$, $\eta_p^2 = .33$. There was no significant effect for an analogous analysis

**Table 3.2** *Training phase mean accuracy for Exps. 1-4*

| | Training Phase Accuracy | | | |
|---|---|---|---|---|
| | Low-Value Target | | High-Value Target | |
| | *M* | SEM | *M* | SEM |
| Exp. 1a | 0.979 | 0.003 | 0.978 | 0.004 |
| Exp. 1b | 0.976 | 0.003 | 0.970 | 0.005 |
| Exp. 2 | 0.963 | 0.007 | 0.968 | 0.007 |
| Exp. 3 | 0.975 | 0.006 | 0.962 | 0.007 |
| Exp. 4 | 0.983 | 0.004 | 0.980 | 0.004 |

of mean accuracy, $t(19) = 0.20$, $p = 85.85$, $\eta_p^2 = .0020$ (compare **Table 3.2** *Training phase mean accuracy for Exps. 1-4*).

*Exp. 1b*

There was neither a significant effect of reward on mean RT, $t(19) = 0.82$, $p = .42$, $\eta_p^2 = .034$, nor on mean accuracy, $t(19) = 1.27$, $p = .22$, $\eta_p^2 = .078$.

*Testing phase*

Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis. This eliminated 6.0% of the data for Exp. 1a and 7.7% for Exp. 1b. **Figure 3.3** plots mean correct

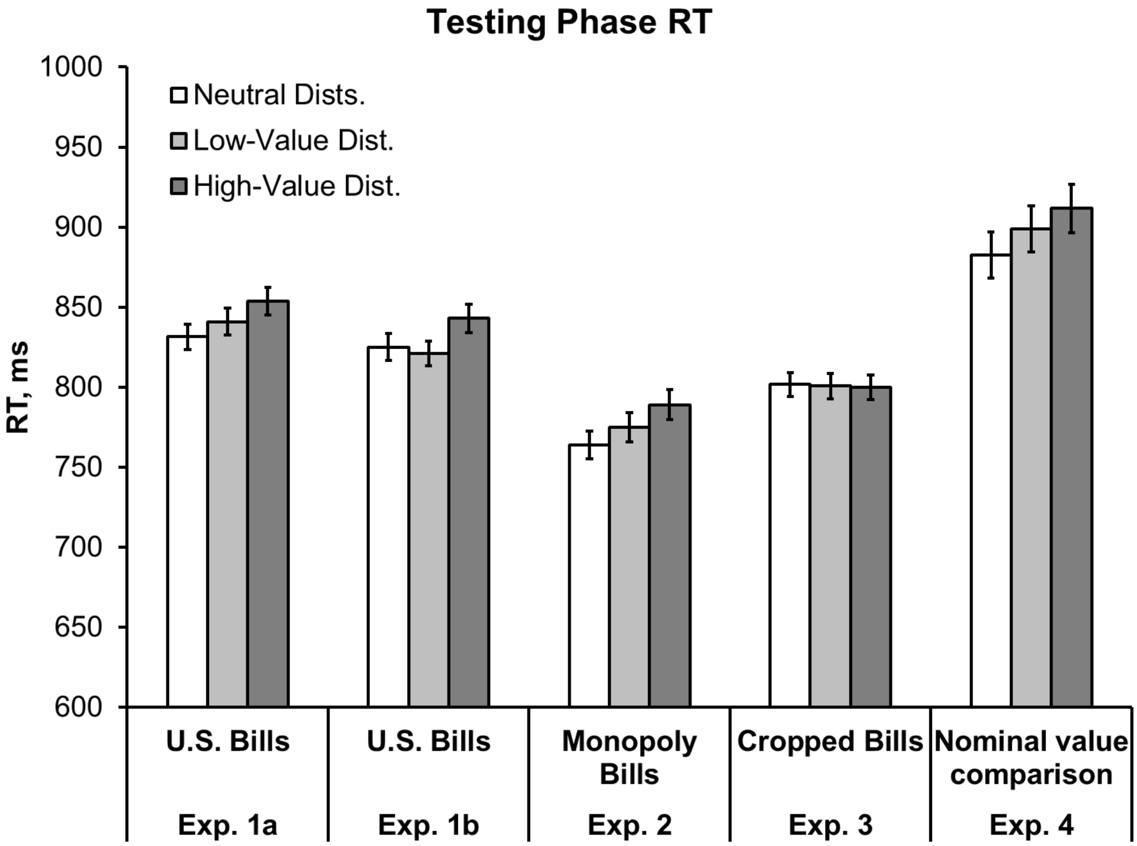

**Figure 3.3** *Testing phase RT*. When colored targets were implicitly associated with images of money during training, the same previously rewarded targets became powerful distractors during a transfer phase. Error bars represent 95% within-subjects confidence intervals (Cousineau, 2005; Franz & Loftus, 2012; Loftus & Masson, 1994; Morey, 2008)

RT for testing trials as a function of distractor value (neutral distractors only, low-value distractor present, and high-value distractor present).

*Exp. 1a*

A one-way repeated-measures ANOVA revealed a significant effect of distractor value, $F(2, 38) = 3.80$, $p = .031$, $\eta_p^2 = 0.37$. Pairwise analyses showed that high-value distractors produced larger RT compared to neutral distractors, $t(19) = 3.26$, $p = .0041$, $\eta_p^2 = 0.36$. The contrasts between high- vs. low-value distractors and between low-value vs. neutral distractors were not significant (all *p*s > .13). There was no significant effect of distractors on mean accuracy, $F(2, 38) = 0.32$, $p = .73$, $\eta_p^2 = 0.084$ (compare see **Table 3.3**).

*Exp. 1b*

A one-way repeated-measures ANOVA revealed a significant effect of distractor value, $F(2, 38) = 3.93$, $p = .028$, $\eta_p^2 = 0.31$. Pairwise analyses showed that participants' responses were slower when a high-value distractor was presented as compared to when a low-value distractor, $t(19) = 2.15$, $p = .045$, $\eta_p^2 = 0.20$, or a neutral distractor was presented, $t(19) = 2.85$, $p = .010$, $\eta_p^2 = 0.30$. The contrast between low-value and neutral distractors was not significant, $t(19) = 0.50$, *p*

**Table 3.3** *Testing phase mean accuracy for Exps. 1-4.*

| | Testing Phase Accuracy | | | | | |
|---|---|---|---|---|---|---|
| | Neutral Distractors | | Low-Value Distractor | | High-Value Distractor | |
| | *M* | SEM | *M* | SEM | *M* | SEM |
| Exp. 1a | 0.983 | 0.003 | 0.979 | 0.005 | 0.978 | 0.004 |
| Exp. 1b | 0.976 | 0.005 | 0.980 | 0.004 | 0.978 | 0.006 |
| Exp. 2 | 0.964 | 0.007 | 0.969 | 0.006 | 0.967 | 0.009 |
| Exp. 3 | 0.964 | 0.007 | 0.967 | 0.006 | 0.967 | 0.009 |
| Exp. 4 | 0.982 | 0.004 | 0.985 | 0.005 | 0.986 | 0.005 |

= .62, $\eta_p^2 = 0.013$. There was no significant effect of distractors on mean accuracy, F(2, 38) = 0.33, $p = .72$, $\eta_p^2 = 0.04$.

### 3.3.3 Task Questionnaire Dataset: The Role of Explicit Task Knowledge

Our results differ from gamified experiments because I show that participants do not need to be motivated or meaningfully engaged in the task to establish VDAC. Our post-experimental questionnaire (see **APPENDIX A**) revealed that participants expressed little desire for either the bills or their associated red/green targets. They admitted to not trying harder as a result of the bills. Additionally, they acquired little knowledge about the purpose of the bills. Participants were at chance when asked to identify which color (red or green) was more likely to predict the $20 bill. Of the twenty participants probed in Exp. 1b, only ten participants chose the correct answer on the two-alternative forced choice question while the other ten guessed incorrectly. When this sample was split based on correct and incorrect guessers, I found no performance differences in the VDAC task between the two groups ($F(2,36) = .103$, $p = .90$, $\eta_p^2 = .006$, see **Figure 3.4**). This suggests, that participants were not engaged in a gamified sense such as in Miranda and Palmer (2014) but they also were not motivated to earn cash such as in paid implementations of the VDAC task (Anderson et al., 2011; Roper et al., 2014). These results imply a very minimal role for motivation and instead stress the importance of the life-long learned history of a rewarding cue.

### 3.3.4 Discussion

When colored targets were implicitly associated with images of U.S. dollar bills during training, the same previously rewarded targets became powerful distractors during a subsequent transfer phase. Specifically, if distractors were presented in a previously highly rewarded color,

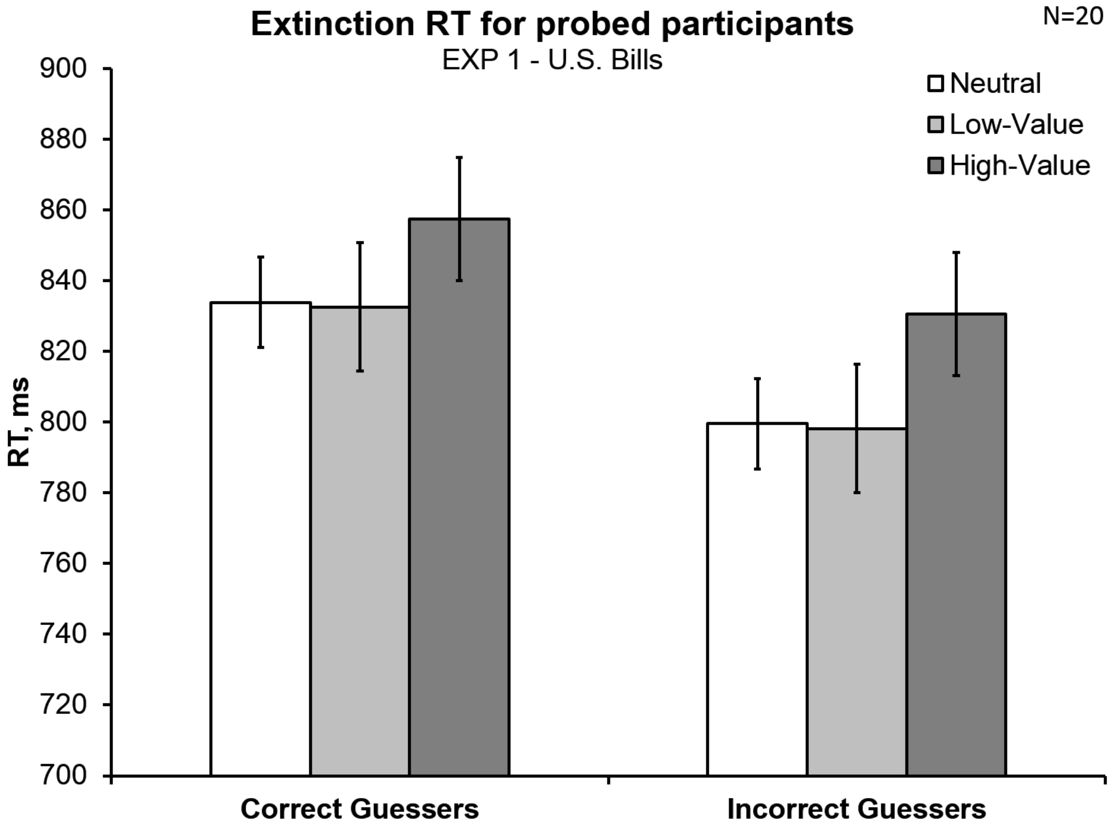

**Figure 3.4** *Testing Phase RT as a function of contingency knowledge.* Ten of the probed participants in Exp. 1 correctly chose the color of the high-value target and ten participants chose incorrectly (see **APPENDIX A**, Task knowledge questionnaire #7). Here we plot RT grouped by participant response and distractor status. Error bars represent 95% within-subjects confidence intervals (Cousineau, 2005; Loftus & Masson, 1994).

participants were slower to search for the diamond compared to when distractors were presented in a neutral or low-rewarded color. Most importantly, the VDAC observed in Experiment 1 was induced by mere exposure to images of dollar bills and in the clear absence of any expected monetary payout. This observation disconfirms the motivated-to-earn hypothesis and provides converging evidence that the VDAC paradigm primarily relies upon Pavlovian conditioning principles (Le Pelley et al., 2015). I observed the effects of bills as facilitation during training (Exp. 1a) and critically as distraction during testing (Exps. 1a & 1b). This finding supports the incentive salience account; participants appeared to consistently seek the color that was associated with a high-value monetary amount. Apparently, VDAC does not directly rely on global motivation, but instead automatically arises out of learned relationships between colors and overlearned secondary reinforcers (Sali et al., 2014).

Money, even as an image divorced from value, is a powerful reward cue. The VDAC effect observed in Experiment 1 is a testament to a lifetime's worth of learning about the transactional utility of money. Our daily interactions with cash build upon each other to form robust reward associations for money. Based on a long history of these interactions, it is likely that the sight of money produces a strong reward signal in the brain (as inferred from Schultz, 2006). This putative reward signal helps us to pursue our goals by allowing us to learn about the cues in our environment. This result provides novel evidence that attention automatically tracks the reward-value of particularly potent secondary reinforcers.

### 3.3.5 Gamification

Gamification is a growing trend in human factors research involving the process of adding an underlying point structure to otherwise mundane computer-based tasks (Deterding, Dixon, Khaled, & Nacke, 2011). Although most rewarded attention studies involve monetary payment, some investigators have introduced game-like features to motivate participant performance and to improve the overall quality of experience in experimental sessions (e.g., Washburn, 2003). Miranda and Palmer (2014) gamified the VDAC task and replaced monetary rewards with points that were doled out on a trial-by-trial basis. For good performance, participants were awarded points and they competed with each other to obtain a place on the high score leader board. Critically, one target color was associated with a high-value bonus modifier and the other was associated with a low-value bonus modifier. When gamified by points, participants reported higher levels of satisfaction and enjoyment, but crucially, no VDAC was obtained. This work compliments Experiments 1a and 1b and together they show that being motivated-to-acquire rewards is neither sufficient nor necessary for VDAC. Experiment 2 was aimed to address the generalizability of the secondary VDAC effect by using images of overlearned game money.

## 3.4 EXPERIMENT 2: MONOPOLY MONEY

Money is endowed by its transactional utility. Early in life, we learn the value of bills and coins by exchanging them for goods and services. We frequently encounter money and are reminded of its utility at the checkout counter, vending machines and ATMs. Regardless of whether we are aware, as adults, we have developed an understanding of the extrinsic value of physical money.

Money has extrinsic value because it is universally accepted as a value-transfer vehicle. Without transactional utility, bills are merely colorful fabric. The physical features of U.S. bills (e.g., rectangular shape, framed border, portrait, prominent numbers in the corners, etc.) make them highly recognizable as instruments of value transfer. Board game currencies, such as Monopoly money, exhibit similar physical characteristics with U.S. bills (compare **Figure 3.2**). In the game Monopoly, players exchange paper notes to buy and sell properties with the objective to bankrupt their opponents. Usually, the player with the most Monopoly money wins the game. Therefore, when playing Monopoly, players are motivated-to-earn game money. I wondered whether Monopoly money, as a unit of value within the game, would produce VDAC in a non-gamified context.

### 3.4.1 Methods

*Participants*

Twenty undergraduates (11 female, mean age = 18.6 years, SD = .89 years, range = 18-20 years) from the University of Iowa psychology research participant pool completed the experiment for partial course credit.

*Stimuli and Design*

Participants viewed grayscale images of game money ($20 and $5 bill) from Hasbro's Monopoly board game. The spatial dimensions of these bill images were identical to the U.S. bill images in Experiment 1. All other task parameters were kept the same as in Experiment 1.

### 3.4.2 Results

*Training phase*

Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 6.9% of the data). Mean correct RT and mean accuracy for training trials were separately computed for high- and low-value reward colors (see **Table 3.1**). There was neither a significant effect of reward on RT, $t(19) = 1.68$, $p = .11$, $\eta_p^2 = .13$, nor on mean accuracy, $t(19) = 1.12$, $p = .34$, $\eta_p^2 = .055$.

*Testing phase*

Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (eliminating 7.0% of the data). A one-way repeated-measures ANOVA revealed a significant effect of distractor value, $F(2, 38) = 5.64$, $p = .007$, $\eta_p^2 = 0.23$. Pairwise analyses indicated that high-value distractors produced larger RT compared to neutral distractors, $t(19) = 3.56$, $p = .002$,

$\eta_p^2 = .40$. No other pairwise comparisons reached significance (all *p*s > .07). Likewise, there was no significant effect on mean accuracy (all *Fs* < 1).

### 3.4.3 Discussion

In Experiment 2, images of Monopoly money produced a VDAC effect that was nearly equivalent to the images of U.S. dollar bills in Experiments 1a and 1b. Monopoly money is likely rewarding because of its physical similarity to U.S. bills. It is also possible that Monopoly money is rewarding due to the socially reinforcing experience of winning at board games. However, this latter claim conflicts with Miranda and Palmer (2014), who found that game points alone failed to produce VDAC. Why then is Monopoly money valued but points are not in a gamified task?

Unlike novel game points, Monopoly money relies on visual similarity to U.S. bills, which possess a long history of learned value. I propose that this reward history is tied to the physical features of bills – a position that is the essence of incentive salience. The physical similarities between U.S. bills and Monopoly money appear to automatically invoke value-based feature weighting. This interpretation suggests that the VDAC effects observed in Experiments 1a, 1b, and 2 rely on a learned history of value (either real-world or in-game) endowed by money-like visual features.

An alternative explanation for the VDAC effect reported here could rely on the sheer magnitude of the numbers presented on the bills. The value of money is conveyed by its denomination and a manipulation of reward (with the help of money or its images) is confounded with a manipulation of nominal value itself. To isolate the role of nominal value, I designed Experiment 3, in which I cropped the images of Monopoly money to remove the contextual elements of the bills (e.g., framed border, prominent values depicted in the corners, etc.). As a result, only the number indicating the value of the bill was visible to participants. If the observed attentional capture effects are merely driven by the outcome magnitude rather than by the implied utility value, then I would expect to observe attentional capture for cropped Monopoly money that is commensurate to standard Monopoly bills. However, if magnitude alone is not sufficient to set the context for value, then I expect to not observe VDAC. Drawing from Miranda and Palmer's (2014) finding that high- and low-value point rewards did not produce VDAC, I hypothesized no VDAC with cropped bills.

## 3.5 EXPERIMENT 3: NOMINAL MAGNITUDE CONTROL

As in previous studies, the reported results so far were value-dependent. Higher magnitude bills produced greater distraction. Experiment 3 was designed to rule out the alternative explanation for my previous results, according to which the nominal value of the bills alone, irrespective of the bills' physical characteristics, modulates VDAC. To this end, I cropped the images of Monopoly money, removing the bills' defining perceptual features and leaving only the nominal value of the bill visible.

### 3.5.1 Methods

*Participants*

Twenty undergraduates (11 female, mean age = 18.7 years, SD = 1.42 years, range = 18-24 years) from the University of Iowa psychology research participant pool completed the experiment for partial course credit.

*Stimuli and Design*

Cropped images of Monopoly money appeared after every correct trial in the training phase. The images were cropped to a size of 4.75˚ high and 4.75˚ wide and displayed at the center of the screen. Only the prominent central values (5 and 20) were visible (see **Figure 3.2**).

### 3.5.2 Results

*Training phase*

Incorrect trials and response latencies ±2.5 SDs of the mean were removed from RT analysis (this eliminated 6.3% of the data). A *t*-test comparing mean RT for high- and low-value reward colors revealed no significant difference, $t(19) = .91$, $p = .37$, $\eta_p^2 = .042$ (see **Table 3.1**). A further *t*-test on mean accuracy (compare **Table 3.2**) revealed that participants performed better in the low-value as compared to the high-value trials, $t(19) = 2.62$, $p = .017$, $\eta_p^2 = .27$.

*Testing phase*

Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 6.2% of the data). Mean correct RT for testing trials were computed as a function of distractor value (i.e., neutral, low, high; see **Figure 3.3**). These data were submitted to a one-way repeated-measures ANOVA. The effect of distractor value was not significant, $F < 1$. Likewise, an analogous ANOVA on mean accuracy (compare **Table 3**) revealed no significant effect of distractor value, $F(2, 38) = .44$, $p = .65$, $\eta_p^2 = .022$.

### 3.5.3 Discussion

In contrast to Experiments 1a, 1b, and 2, there was no VDAC observed in Experiment 3. Thus, there is no evidence for a VDAC effect based on nominal value alone. This finding strongly suggests that the VDAC effects observed in Experiments 1-2 are attached to reward value rather than on sheer magnitude alone. As hypothesized, the bills' characteristic perceptual features seem to be necessary to observe VDAC, implicating a strong and overlearned reward value of bills. I observed a slight accuracy advantage for the low-value condition in training, but accuracy was generally at ceiling suggesting response accuracy trade-offs were minimal if present at all.

Together, these results support the theme that attention can be biased in accordance with principles of Pavlovian conditioning. Learned stimulus-reward associations turn mere images of U.S. dollar and Monopoly bills into powerful rewarding stimuli that can induce reliable attentional capture effects themselves. Moreover, those effects seem to be due to the depiction of the global configuration of the bill rather than on the depiction of magnitude alone. To further support this claim I designed Experiment 4, which directly tested the effects of monetary value vs. mere nominal value in a within-subject design.

## 3.6 EXPERIMENT 4: CROSS-CATEGORY COMPARISON

In Experiment 4, I chose a slightly different approach. That is, I examined the rewarding effects of U.S. bills while holding nominal value constant. Participants viewed either an image of a $20 bill (compare Exps. 1a and 1b in **Figure 3.2**) or an image of the number 20, cropped from a Monopoly bill image (compare Exp. 3 in **Figure 3.2**). This allowed me to directly test the effects of monetary value vs. mere nominal value in a within-subject design. Based on the results of Experiments 1-3, I expected to observe VDAC for distractor colors that were previously associated with the $20 bill image. In contrast, no VDAC should be obtained if the distractor color was previously associated with an image from a cropped Monopoly bill.

### 3.6.1 Methods

#### *Participants*

Twenty undergraduates (12 female, mean age = 18.85 years, SD = 1.63 years, age range = 18-25 years) from the University of Iowa psychology research participant pool completed the experiment for partial course credit.

### *Stimuli and Design*

Experiment 4 was virtually identical to Experiment 1a except for the low-reward condition. That is, while in the high-reward condition an image of a $20 dollar bill was shown (compare Exps. 1a and 1b in **Figure 3.2**), in the low-reward condition the image of a cropped Monopoly 20 was presented (compare Exp. 3 in **Figure 3.2**). Analogous to previous experiments, I employed a 20/80 percent reward contingency assignment to target colors (red/green). In Experiment 4, this meant that both target colors were sometimes associated with U.S. bills and sometimes associated with nominal value.

## 3.6.2 Results

### *Training phase*

Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (eliminating 3.6% of the data). There were no significant effects of reward, neither for mean RT, $t(19) = 1.77$, $p = .093$, $\eta_p^2 = .14$ (see **Table 3.1**) nor for mean accuracy, $t(19) = .93$, $p = .37$, $\eta_p^2 = .043$ (see **Table 3.2**).

### *Testing phase*

Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (eliminating 3.4% of the data). Figure 3 depicts mean RT as a function of reward (neutral, low, high). A one-way repeated-measures ANOVA revealed a significant effect of distractor value, $F(2,38) = 4.48$, $p = .026$, $\eta_p^2 = 0.33$. Pairwise analyses further showed that high-value distractors produced larger RT compared to neutral distractors, $t(19) = 2.91$, $p = .0090$, $\eta_p^2 = .31$. No other pairwise comparisons reached significance (all *p*s > .18). Likewise, there was no significant effect on mean accuracy (*F* < 1).

### 3.6.3 Discussion

Participants were captured by the color previously associated with the $20 U.S. bill but not captured by the color previously associated with the nominal value. The results of Experiment 4 provide strong evidence that the capture effects observed in Experiments 1-3 are due to the physical features of bills and not their nominal value alone. This implies a necessary role of perceived value before observing implicit reward effects.

## 3.7 CHAPTER DISCUSSION

In the experiments presented herein I investigated the influence that money, as a reward-signaling stimulus, has on attention. Importantly, monetary income was not used as a reward because participants were never paid. Instead, money was visually presented as a 2D image on a computer screen. Hence, I dissociated the sensory elements of money from the motivation to obtain cash. Remarkably, the bill images established reliable stimulus-reward associations. That is, distractor colors that were associated with images of dollar bills during training became powerful distractors during a transfer phase. Apparently, the sensory information conveyed by the image of money is strong enough to be rewarding, presumably because of the bills' overlearned reward history. This suggests the results from paid VDAC studies are not necessarily based on an expected cash payout. Further support for this argument is that our finding generalized to images of Monopoly money, which share visual features with U.S. dollar bills. Taken together, this clearly indicates that a real-life utility of the manipulated reward is not necessary in the VDAC task. In addition, I demonstrated that VDAC is not dependent on the sheer magnitude of the numbers depicted on bills. Instead, it seems at least some bill-like elements must be present in order to observe these implicit reward effects.

The rewarding influence of monetary images on attention and behavior seems to be automatic and independent of participants' awareness[1]. That is, participants performed at chance levels when they were asked to indicate which of the two target colors (red or green) most often preceded high-value bills. This indicates that participants are prone to value-driven attentional capture even when they are explicitly unaware of the underlying stimulus-reward associations (for a similar conclusion see Seitz, Kim, & Watanabe, 2009). These results stress the role of automatic value-judgements in attentional learning and downplay the motivational drive to obtain cash prizes (c.f. Della Libera, Perlato, & Chelazzi, 2011; Engelmann, Damaraju, Padmala, & Pessoa, 2009; Hübner, & Schlösser, 2010; Sali et al., 2014). Furthermore, my results show that VDAC operates incidentally without the need to engage participants by using explicit game-like tactics (c.f. Miranda & Palmer, 2014).

Although gamification can be used as a helpful motivation tool, nearly all forms of gamification introduce demand characteristics (Washburn, 2003). In gamifying an experiment, participants are explicitly encouraged to develop strategic behaviors which may contradict how they would otherwise naturally behave. Because the process of gamifying experiments can potentially increase the overall well-being and interest of student-participants, gamification is a field worthy of pursuit (Miranda & Palmer, 2014). However, it is clear that gamification does not necessarily increase performance metrics (Hawkins, Rae, Nesbitt, & Brown, 2013). In fact, with

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[1] I should specify that these processes likely unfold automatically only to the extent that an individual has sufficiently overlearned the reward value of the chosen currency.

these additional demand characteristics, gamification may contravene the researcher's goals and could confound the results. Therefore, caution should be exercised when gamifying tasks. Gamification protocols that are implemented willy-nilly may initially engage attention but such haphazard designs may produce counterproductive results in the long run. The results of **Chapter 3** suggest that frequently perceived rewards are sufficient to induce attentional engagement, but it is unclear whether images of money would persistently guide attention to be effective in the industrial setting.

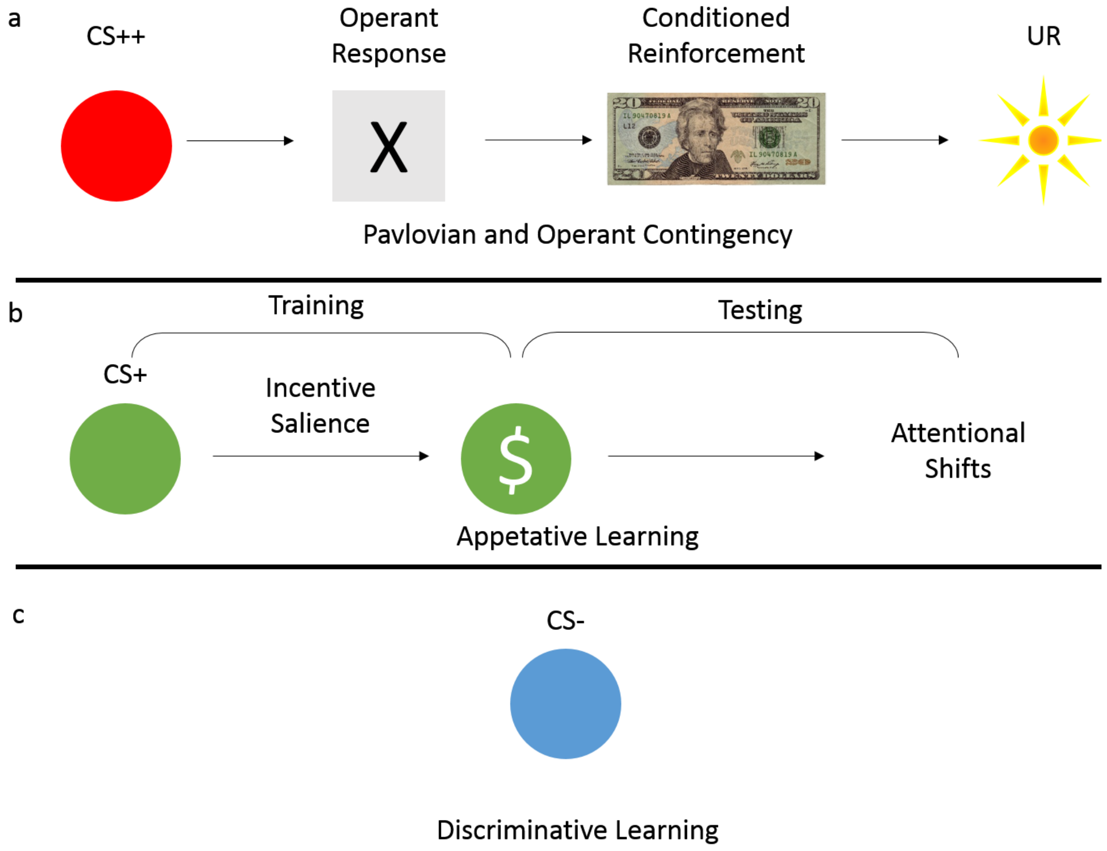

**Figure 3.5** *Pavlovian and operant characteristics of the VDAC paradigm.* The experiments discussed herein take advantage of this hybrid instrumental design. UR = unconditioned response. *b) Appetative learning.* Target stimuli undergo incentive salience and subsequently captures attention. *c) Discriminative learning.* Colors are associated with a high-value (CS++), low-value (CS+), or neutral value (CS-). Participants learn to discriminate between colors that predict reward and neutral colors

### 3.7.1 VDAC is Highly Pavlovian

If VDAC is meant to measure incentive salience as described in drug addiction (Anderson et al., 2013), then I would expect VDAC to heavily rely on Pavlovian conditioning (rf. Panel b in **Figure 3.5**). Whether or not VDAC can serve as a proxy for incentive salience is an open question, although some evidence has begun to accumulate (Le Pelley et al., 2015; Pearson et al., 2015). The results of our study provide converging evidence with a recent study that demonstrated that rewards can sometimes lead to attentional capture even when the rewarded features are always task-irrelevant. Le Pelley and colleagues (2015) modified Anderson's (2011) original VDAC paradigm so that rewards were implicitly paired with the color of a salient distractor. Rather than employing a training phase and a testing phase, they used a single phase where participants searched for a gray square amongst gray circles. Participants were paid a small monetary amount (10¢ or 1¢) on a trial-by-trial basis for fast, correct responses to discriminate the orientation of a line within the target square. A salient color distractor was present on a proportion of trials. The color of this distractor was associated with either high-value or low-value reward. Critically, unlike the original VDAC design, these distractors never served as targets. Thus, the rewarded distractor was always task-irrelevant. Because rewards were performance-contingent, paying attention to the distractor resulted in reduced monetary gains. The authors argued that if VDAC relies on Pavlovian principles, then high-value distractors should produce greater attentional capture than low-value distractors. Alternatively, they argued if VDAC relies of operant principles, then attention should be indifferent to the specific color-reward associations. They observed better accuracy when the distractor was associated with low-value than with high-value. Therefore, participants were captured by the high-value distractor more than the low-value distractor despite these distractor colors never having been task-relevant. This observation implies that VDAC largely arises from

Pavlovian rather than operant, conditioning. My current results compliment this work by providing converging evidence that VDAC arises from the sheer statistical co-occurrence of colored targets and secondary reinforcers during a training phase.

### 3.7.2 Social Rewards

Social cues can help convey human emotion. The face in particular is special because of its ability to express various internal states. Facial behaviors such as smiling can often be rewarding for both the smiler and the observer. A recent study examined the effects of cartoon faces as rewards by selectively pairing them with colored targets (Anderson, 2015). One color was associated with a high probability (80%) of a smiley face and a low probability (20%) of a neutral face. Anderson found that stimuli previously associated with smiley faces capture attention when presented as irrelevant distractors. This finding suggests that the attentional system can operate on social rewards in addition to primary reinforcers like food or secondary reinforcers like money.

## 3.8 CHAPTER CONCLUSION

When motivated to achieve a desired state, attention can be directed toward informative cues. This information gradient provides the basis for value representation in the brain (Gottlieb, 2012). Attention filters incoming information and allows only the most pertinent representations to carry on. Pertinence in turn is determined by the environmental context (e.g., Cosman & Vecera, 2013) and by internal states. For instance, street signs and traffic signals are pertinent when navigating an urban city, but rocks and rivers are pertinent when hiking in the wilderness. Food cues are pertinent when we are hungry, but water cues are pertinent when we are thirsty. Environmental events that are correlated with desirable outcomes become powerful cues that acquire pertinence and thus influence attention and subsequent behavior. Classic studies on reinforcement learning (Skinner, 1938; Thorndike, 1911) and the contemporary sentiment on value-driven attention (Anderson, 2013; Gottlieb, 2012; Le Pelley et al., 2015; Sali et al., 2014) support this view.

In conclusion, lifelong monetary reinforcers exert noticeable effects on attentional processes. Moreover, I have demonstrated that this effect generalizes to secondary reinforcers that are not canonical vehicles of value transfer but nonetheless familiar (i.e., Monopoly money). I propose that cue pertinence is set by reward history and doesn’t directly rely on motivation to earn rewards. Furthermore, it is likely that mere images of whole categories of rewarding stimuli (e.g., food, consumer merchandise, pornography, alcohol and drugs, etc.) have a substantial impact on attentional selection. The implications of this effect are compounded by the over-abundance of distractions that accompany modern day living. Lastly, my findings allow saving resources in an experimental context. That is, researchers who are interested in studying the effect of money and reward on behavior can use images of bills to manipulate reward as VDAC can be induced gratis.

# 4 TRACKING THE ECONOMY OF VISUAL ATTENTION

## 4.1 THE ATTENTIONAL HOMUNCULUS AS AN ECONOMIC ACTOR

The environment is filled with uncertainty and overt behavior is resource consuming. Therefore, decisions have to be made in an economical manner. If we imagine the attentional homunculus as a proxy for reward-based feature weighting, then how might the homunculus act in economic situations? On one hand, the homunculus could boost the gain to stimulus features according to expected utility. In this way, the homunculus acts as a fastidious *bean-counter*, faithfully tracking the values of rewards in the environment. On the other hand, the homunculus might be a *fuzzy mathematician* if the deployment of attention does not uniformly scale with predicted rewards. In **Chapter 3**, I first outline the theoretical and empirical support for these two competing hypotheses. Then, I introduce a new experimental paradigm, the reward contingent capture paradigm, and show how it can help unravel the underlying economic pattern of reward's impact on attention.

## 4.2 THE RATIONAL HOMUNCULUS: A BEAN COUNTER

The theoretical support for the bean counter account largely comes from *expected utility theory* (von Neumann & Morgenstern, 2007). Expected utility theory is a normative characterization of rational economic decision-making. It is important to note that expected utility theory is meant to encompass explicit decision-making behavior and thus describes higher level processing compared to visual attention. However, there is empirical support for visual attention-like analogues in animal learning. For example, *matching law* and *maximizing* describe operant choice behavior in a variety of settings including key-pecking in pigeons (Baum, 1974) and wheel running in rats (Belke & Heyman, 1994). Like VDAC, maximizing accounts for economic behavior by appealing to trial-by-trial adjustments in associative strength (Rescorla & Wagner, 1972). Exposure-based methodologies like those used in matching law work have clear parallels with human perceptual exposure methodologies used in *statistical learning* (Choi & Watanabe, 2009) whereby human observers have been shown to be incredibly reliable in implicitly tracking object frequencies in the environment. In the paragraphs that follow, I present the basis for the rational homunculus.

### 4.2.1 Expected Utility Theory

One of the earliest methods of examining economic decision-making was to invoke the concept of a lottery (von Neumann & Morgenstern, 2007). Theorists envisioned how a lottery winner might behave when given the choice between two different payoffs. Critically, the payoffs varied in their risk and magnitude profiles. It is under these conditions that von Neumann and Morgenstern theorized how a rational economic actor should behave. Expected utility theory is based upon four axioms that define how the rational decision-maker would behave when faced with economic uncertainty (von Neumann & Morgenstern, 2007). The *completeness axiom* assumes that the economic actor can freely choose between the available outcomes. When given two options, A and B, actors can choose option A over option B, be indifferent to the outcomes, or choose option B over option A. The *transitivity axiom* assumes that the actor is consistent in his choices and will always choose the outcome that affords the greatest expected utility. The *continuity axiom* assumes that if option A is preferred to option B and option B is preferred to a third option C, then there exists some combination of options A and C such that actors are indifferent between choosing a ratio of options A and C versus option B alone. The *independence axiom* assumes that preferred outcomes will always be preferred even when accompanied by additional, less desirable outcomes. In other words, the independence axiom says that if option A is preferred to option B, then the addition of a third undesirable option C should not affect the actor's preference of option A. Expected utility can be computed as follows:

$$EU_A = p_A * m_A \,, \tag{1}$$

where EU represents expected utility of option A, p is the probability of reward to option A, and m is the magnitude of the reward to option A.

### 4.2.2 Matching Law

Matching Law elegantly describes the observed relationship between rewards and choice behavior in animals (de Villiers, 1977; Herrnstein, 1974). Briefly, it describes how the distribution of responses matches the distribution of rewards. In matching law studies, different cues are employed, each associated with a unique variable reinforcement schedule. The rates of responding (e.g., pecks, button-presses, or licks) are measured for each cue to determine the animals' preference for the cues. The finding is that animals' choice behavior faithfully mirrors the availability of rewards. Matching law can be expressed as a ratio of proportions:

$$\frac{R_A}{R_A+R_B} = \frac{EU_A}{EU_A+EU_B}, \tag{2}$$

where R is the rate of responses to options A and B respectively. Specifically, Matching Law states that the number of responses to option A divided by the total number of the responses is proportional to the rewards available on option A divided by the total availability of reward (see Equation 2).

Paradigmatically, matching law studies share affinity with expected utility theory because they satisfy the completeness axiom; in matching tasks, animals are free to respond to two perceptually unique cues (option A and option B). The critical difference between matching law and expected utility theory, however, is that matching law is a descriptive account of animal behavior. Animals cannot easily heed complex verbal instructions and cannot readily interpret text descriptions such as the lottery examples discussed in expected utility theory. Thus the animal is forced to implicitly learn the specific reinforcement schedules via direct, on-line exposure with the reward payoffs.

### 4.2.3 Maximizing

It is helpful to think about matching as the ability of the system to distribute decisional weights to various available options (Rescorla & Wagner, 1972). These decision weights are influenced by several factors (e.g., reward magnitude, reward probability, delay time until reward, etc.). Maximizing describes how animals are able to effectively monitor these factors to maximize gains and minimize losses. In contrast to matching law, maximizing provides a mechanistic account for instrumental behavior. The maximizing mechanism of trial-by-trial accrual of information shares affinity with mechanistic accounts of statistical learning and VDAC (Hickey, Chelazzi, & Theeuwes, 2010).

### 4.2.4 Statistical Learning

Learning is often associated with high-level decision-making rather than low-level sensory processes. It is often falsely assumed that perceptual processes are not subject to training. In fact, there is much evidence to suggest that the efficiency of sensory processing is enhanced with structured experience. For example, in one visual statistical learning experiment observers passively viewed shapes presented in triplets (Turk-Browne, Jungé, & Scholl, 2005). The experimenters manipulated the frequency with which certain conjunctions of shapes appeared in the triplets. Some conjunctions were presented more often than others. In a later task, observers showed RT facilitation for the more frequent conjunctions. Furthermore, this effect scaled with the frequency of the conjunctions which suggests that the visual system is extraordinarily capable in faithfully tracking first- and second-order object relationships in the environment. This is a common theme in many other recent studies on visual perceptual learning (Cosman & Vecera, 2014; Fiser & Aslin, 2005; Zhao, Cosman, Vatterott, Gupta, & Vecera, 2014). The evidence from statistical learning supports the rational homunculus.

## 4.3 THE IRRATIONAL HOMUNCULUS: A FUZZY MATHEMATICIAN

In contrast to the bean counter, the attentional homunculus may be a fuzzy mathematician. *The Allais paradox* describes how human behavior violates fundamental assumptions (Allais, 1953) resulting in the probability distortions that are currently a staple in the field of behavioral economics.  More recent models, such as *prospect theory*, use these probability distortions to account for both risk seeking and risk avoidance patterns observed in humans. Below, I describe how empirical evidence sometimes violates the assumptions of expected utility theory.

### 4.3.1 The Allais Paradox

The Allais paradox (Allais, 1953) describes a violation of the independence axiom assumed by expected utility theory. To demonstrate the paradox, Allais asked participants to choose between a series of lottery options (see **Table 4.1**). In the first lottery, option 1A is a sure thing (100% chance of winning $1M) and option 1B is a gamble (89% of winning $1M, 10% chance of winning $5M, and 1% chance of winning $0). In lottery 1, the sure thing, option 1A, is preferred

**Table 4.1** *Allais paradox example lotteries.*

| Lottery 1 | | | | Lottery 2 | | | |
|---|---|---|---|---|---|---|---|
| Option 1A | | Option 1B | | Option 2A | | Option 2B | |
| Prize | Chance | Prize | Chance | Prize | Chance | Prize | Chance |
| $1M | 100% | $1M | 89% | $0 | 89% | $0 | 90% |
| | | $5M | 10% | | | | |
| | | $0 | 1% | $1M | 11% | $5M | 10% |

to option 1B. This is in spite of the fact that option 1A has a smaller expected utility than option 1B. In the second lottery, both options were gambles (see lottery 2 in **Table 4.1**). Most participants choose option 2B, in which the chances for winning were smaller but the expected value was greater than for option 2A.

Allais argued that it was reasonable to choose option 1A given option 1B, and further that it was reasonable to choose option 2B given option 2A. However, participants who choose option 1A and then choose option 2B are not behaving consistently across the lotteries. To satisfy the independence axiom a participant would have to choose option 1A and option 2A or option 1B and option 2B. In other words, a participant should either make preferences based on the chance of winning alone or on the expected value alone. When participants choose based on chance of winning in lottery 1 and based of expected value in lottery 2, they violate the independence axiom. More broadly, the two lotteries differ in their psychological framing and consequently participants treat the options differently (Allais, 1953). The Allais paradox and other framing effects provide the basis for prospect theory.

### 4.3.2 Prospect Theory

Prospect theory is a four-fold account of economic choice that splits gains and losses across a reference point (Kahneman & Tversky, 1979). Analogous to the Allais paradox, the common finding is that participants' economic choice behavior is susceptible to framing effects. For instance, lottery 3 has two options (see lottery 3 in **Table 4.2**). The options in lottery 3 have equal expected utility, but option 3A is a sure thing and option 3B is a gamble. Empirically, option 3B is preferred. Lottery 4 is mathematically equivalent to lottery 3 multiplied by a factor of 1,000,000. Here, participants are more likely to prefer option 4A, the sure thing. This shows that participants are risk-seeking at small expected utilities and risk-averse at high expected utilities, which is yet another violation of the independence axiom.

**Table 4.2** *Prospect theory gained-framed example lotteries.*

| Lottery 3 | | | | Lottery 4 | | | |
|---|---|---|---|---|---|---|---|
| Option 3A | | Option 3B | | Option 4A | | Option 4B | |
| Prize | Chance | Prize | Chance | Prize | Chance | Prize | Chance |
| $1 | 100% | $0 | 90% | $1M | 100% | $0 | 90% |
| | | $10 | 10% | | | $10M | 10% |

This observation, however, is only half of prospect theory. When framed as losses, behavioral observations reveal another violation of independence. For example, **Table 4.3** depicts a series of lotteries (ref. penalties) framed as losses instead of gains. Each option represents the amount that a participant would hypothetically lose. Participants were free to choose between two options in each penalty. Penalties 5 and 6 are the mathematical inverses of lotteries 3 and 4 (i.e., the options in each penalty are equivalent and penalty 6 is 1,000,000x greater than penalty 5). Empirically, participants choose the sure (100%) loss of a dollar (option 5A) over the risky (10%) chance to lose 10 dollars (option 5B), which suggests risk aversion for low-value losses. In contrast, for high-value losses, the risky loss (option 6B) is preferred over the sure loss (option 6A), which implies risk-seeking behavior.

**Table 4.3** *Prospect theory loss-framed penalties.*

| Penalty 5 | | | | Penalty 6 | | | |
|---|---|---|---|---|---|---|---|
| Option 5A | | Option 5B | | Option 6A | | Option 6B | |
| Loss | Chance | Loss | Chance | Loss | Chance | Loss | Chance |
| -$1 | 100% | $0 | 90% | -$1M | 100% | $0 | 90% |
| | | -$10 | 10% | | | -$10M | 10% |

On their own, the differences between penalty 5 and penalty 6 represent a violation of independence. Additionally, the more unique contribution of prospect theory is that by comparing losses to gains we can observe another, higher-order violation of independence representing a three-way interaction between risk, expected utility, and gain/loss reference frame. Independence would allow risk-seeking or risk-averse behavior alone, but it cannot account for the unique pattern observed -- risk-seeking for low gains and high losses and at the same time being risk-averse for low losses and high gains.

### 4.3.3 Subjective monetary value questionnaire dataset

To gauge the subjective value of certain U.S. dollar amounts in my sample population, I asked participants to complete a series of questions that resembled the lotteries of prospect theory (see **APPENDIX B**). In total, three separate surveys were administered – a survey for low-gamble

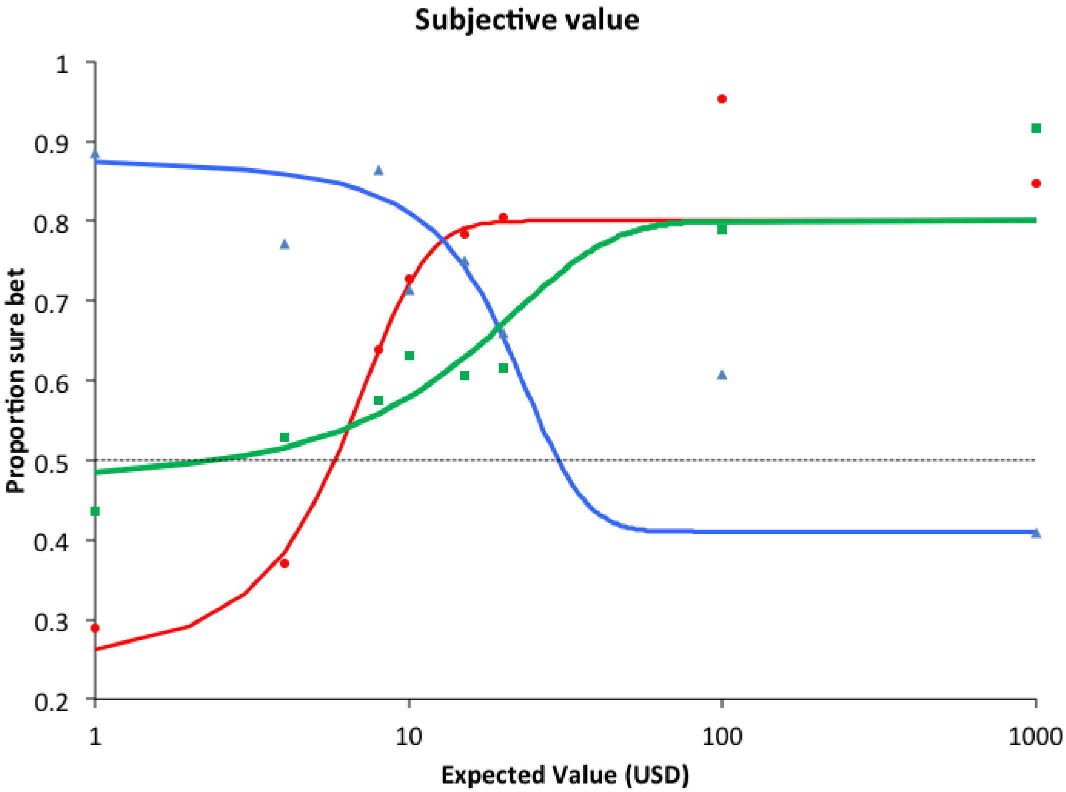

**Figure 4.1** *Subjective monetary value questionnaire dataset*. Participants completed a series of questions that resembled the lotteries used in prospect theory. Example lotteries can be found in **APPENDIX B**. Three unique series of questions were asked – high gamble gains (red line), low gamble gains (green line), and high gamble losses (blue line). For each lottery, two options were provided. The options were always equal in expected utility value, however, one option was always a sure thing and the other was a gamble. The dotted line represents the predictions of expected utility theory

gains, another for high-gamble gains, and a third survey for high-gamble losses. The lotteries included a pair of choices for each of the following U.S. dollar amounts: 1, 2, 4, 8, 12, 15, 20, 100, and 1000. **Figure 4.1** depicts the preference of participants to choose the sure bet as a function of the following factors: risk-profile, expected utility, and reference frame. The green line is a low-gamble gain (sure gain vs. 50% chance to win), the red line is a high-gamble (sure gain vs. 10% chance to win), and the blue line is a high-gamble loss (sure loss vs. 10% chance to lose).

The results represent the classic distortions in responses. That is, participants were risk-seeking at low gains and high losses but risk averse at high gains and low losses. Furthermore, these data demonstrate that for high gamble gains, the point of subjective equality for a gamble vs. a sure gain is somewhere around $8.

From prospect theory we can infer that high-level economic decision-making is typically irrational in the strictest interpretation of expected utility theory. This inference supports the fuzzy mathematician, but only peripherally due to the explicit nature of lottery-inspired experimental paradigms. There is however, empirical evidence from primate research that demonstrates clear violations of independence despite animals implicitly learning the tasks (Stauffer, Lak, Bossaerts, & Schultz, 2015).

### 4.3.4 Nonlinear reward probability distortions in primates

A recent study on economic choice in macaque monkeys revealed evidence of probability distortions in the processing of rewards and risks (Stauffer et al., 2015). Monkeys viewed a pair of textured circles and were forced to choose between the two by making a saccade toward one stimulus or the other. Monkeys were given blackcurrant juice on a per-trial basis depending on which circle they chose. Segments of the circles were textured to indicate the size of the associated reward. Additionally, the texture’s orientation indicated the probability of the reward. Over the course of the experiment, the animals consistently chose the stimulus that had features indicating high reward magnitude and high reward probability. However, the animals’ choice behavior also reflected non-linear distortions in reward probability weighting. The animals were insensitive to small changes in reward probability at the extreme ends of the scale. That is to say that an increase in reward probability did not result in a proportional increase in the animals’ preference. The pattern rather resembled a traditional s-curve (c.f. **Figure 4.1**) which indicates the monkeys underweighted high probabilities and overweighted low probabilities. Thus, in accordance with prospect theory, the animals were risk-seeking at low expected values.

## 4.4 INTERIM SUMMARY

On the one hand, the Allais paradox, prospect theory, and primate research support the idea of an irrational attentional homunculus. On the other hand, expected utility theory, matching law, and statistical learning support the idea of a bean-counting homunculus. Furthermore, there has been no systematic test of the economic behavior of human visual attention. In the paragraphs that follow, I describe how extant paradigms are not well-suited to systematically address the relative attentional value of complex reward schedules. I then introduce a new visual attention paradigm - the RCC task - that was designed to better satisfy the constraints of expected utility theory without compromising the Pavlovian conditioning aspects of the VDAC paradigm or the use of secondary reinforcement.

## 4.5 MAPPING UTILITY SPACE

Two factors, reward magnitude and reward probability, are used to calculate expected utility (see **Equation 1**). In order to investigate whether the attentional homunculus acts like a rational bean counter or a fuzzy mathematician, these two factors must be decoupled and analyzed independently. A bean counter would always prefer a higher expected reward value, regardless of other factors. In contrast, a fuzzy mathematician might be biased by factors other than the expected value. For instance, the mere magnitude of reward or the overall probability to receive a reward might be of interest. **Figure 4.2** depicts expected utility (e.g., \$4, \$8) as a function of reward magnitude and probability.

The canonical VDAC paradigm usually focuses on exposing effects of reward in general, with little regard for possible differential effects of expected value, magnitude, and probability. That is, specific colors get associated with compound schedules of reinforcement that combine a high expected utility with a high probability of a high magnitude of reward (compare **Figure 4.2**). For instance, the color red is rewarded with 10¢ in 80% of correct trials (ref., point G in **Figure 4.2**) and 2¢ in 20% of correct trials (ref., point C). Likewise, the color green is rewarded with 2¢ in 80% of correct trials (ref., point E) and with 10¢ in 20% of correct trials (ref., point F). Thus, reward magnitude and reward probability are confounded in the construction of high- and low-

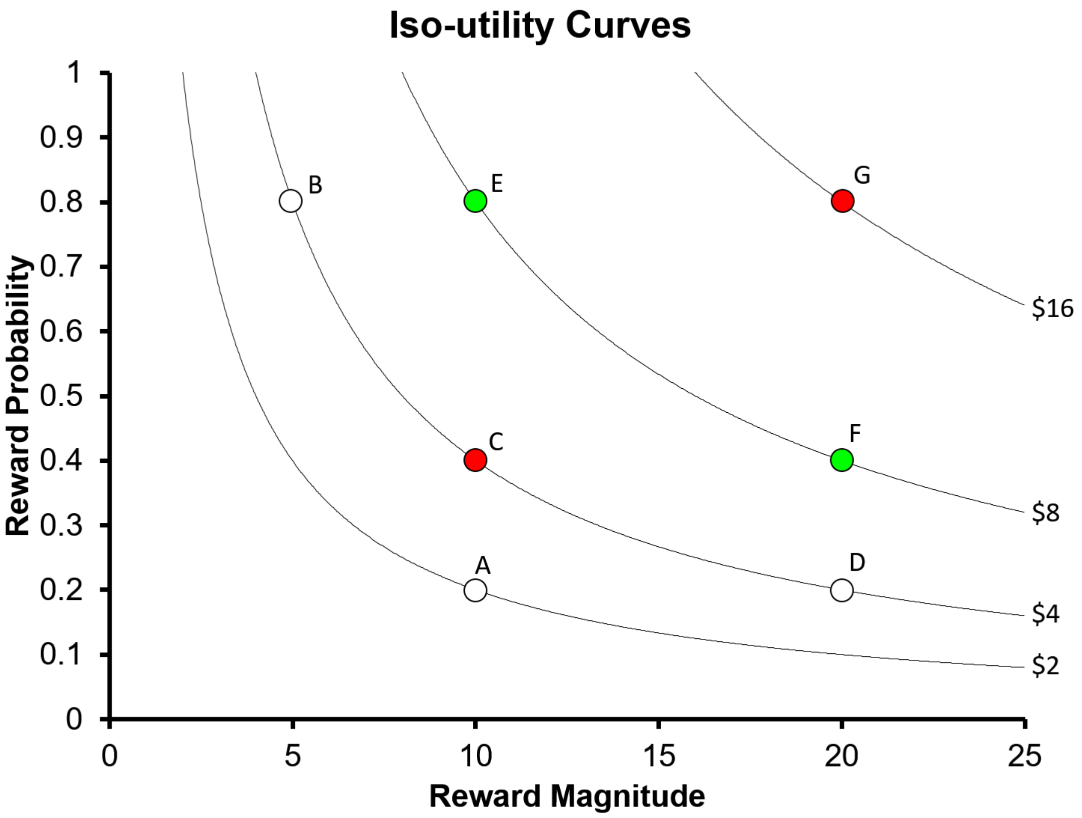

**Figure 4.2** *Map of utility space.* Economic decisions are made according to reward magnitude and reward probability. The curves depicted in this figure represent iso-utility functions – that is every point along each curve has the same expected utility value. In **Chapter 3**, high-value reward was associated with the red points (C and G) while the low-value reward was associated with the green points (E and F). The points A-G were used as schedules of reinforcement in **Chapter 4**

value schedules. Therefore, it is thus unclear from previous VDAC tasks whether attentional capture is influenced by the difference in expected value (i.e., bean counter) or instead by a psychological mixture of reward magnitude or probability (fuzzy mathematician). In order to distinguish between those two possibilities, I sought to construct conditions in which reward magnitude and reward probability are manipulated while the expected value is held constant over conditions.

The animal learning literature has shown that reward magnitude and reward probability are used to inform an organism's choice behavior (Baum, 1981). When two buttons are variably reinforced, animals chose the one that gives large rewards more than the one that conveys small rewards. Likewise, animals chose the button that more frequently delivers reward over an alternative that rarely leads to reward. Matching law paradigms share affinity with the lottery paradigm described above because they both satisfy the completeness axiom -- animals are free to choose from two available options. The reward contingent capture paradigm also satisfies these constraints.

## 4.6 REWARD CONTINGENT CAPTURE PARADIGM

The core concept of the *reward contingent capture* (RCC) task is similar to the VDAC task. In a training phase, stimulus-reward associations are established by differentially reinforcing specific colors. In a later testing phase, those associations are measured by assessing their impact on attentional capture. The RCC task differs from the VDAC task however, for several, crucial reasons. First, the RCC task derives from the contingent cuing task (c.f., Folk et al., 2015; Folk, Remington, & Johnston, 1992) rather than a visual search task. Second, reward-associated colors are task-irrelevant during training – participants search for the target on the basis of shape alone but are rewarded on the basis of target color. More specifically, in the training phase of the VDAC

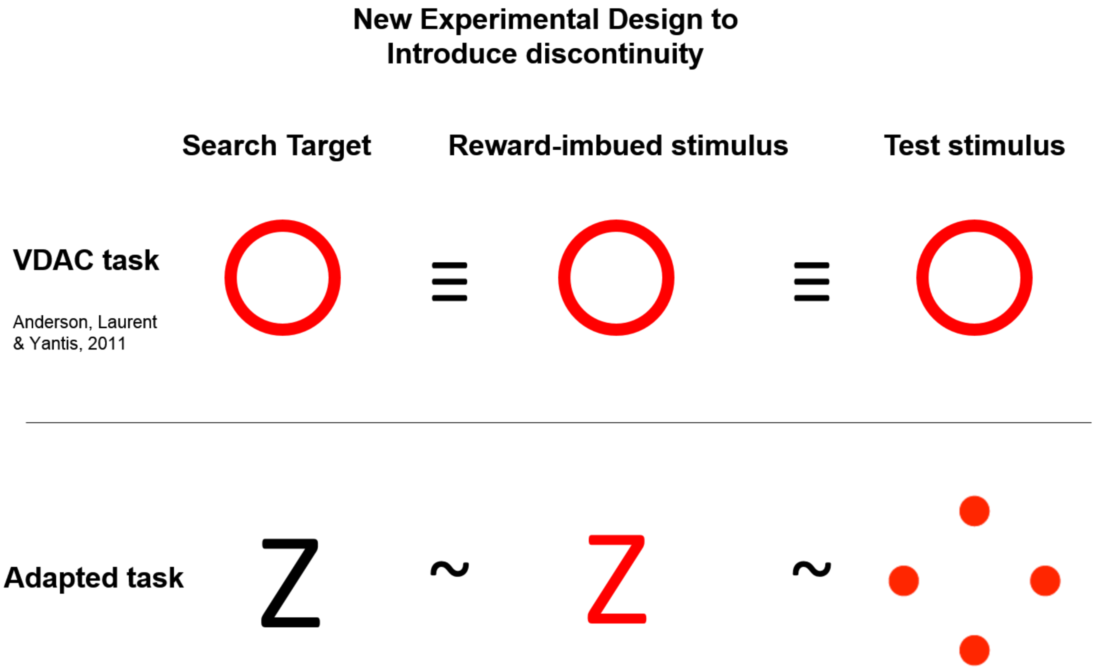

**Figure 4.3** *New experimental design to introduce stimulus discontinuity.* In the value-driven attentional capture task, the search target during training is a red (or green) circle. Rewards are probabilistically associated with this target. In the testing phase, then same stimulus appears as a distractor. Therefore the search template is identical to the reward-imbued stimulus which is identical to the test stimulus. In the reward contingent capture task, this continuity is broken. The test stimulus shares only one thing in common with the search target – color. Furthermore, rewards are contingent on this shared color and nothing else

task participants explicitly search for reward-associated colors (i.e., green and red), but in the RCC task participants search for an X- or Z-shaped target and thus can ignore reward-associated colors (see **Figure 4.3**). Finally, the testing phase of the RCC task is uniquely setup to satisfy the completeness axiom. Specifically, in the testing phase every trial represents a two-alternative economic choice between a previously experienced color (reward-neutral or reward-imbued) and a novel color. This setup resembles the lottery paradigm and matching tasks in that the economic actor is free to choose between two available options. In the RCC task, attention can prefer the rewarded color, the novel color, or be indifferent to the colors. In the way, an attentional choice can be operationally defined as a spatial cuing effect. Faster RT for valid trials than invalid trials, represents attentional selection of the color in question. Therefore, the RCC task reveals selection for the previously rewarded color when there is a valid cuing effect, selection for the novel color when there is an inverse cuing effect, and indifference to the colors when there is no cuing effect.

## 4.7 EXPERIMENT 5: STRONG TEST OF EXPECTED UTILITY THEORY

There are many findings that provide confirmatory evidence for an economically rational attentional homunculus, but none that specifically set out to falsify the expected utility account. In Experiment 5, I orthogonally crossed reward magnitude and reward probability and chose two points (option $10@80% and option $20@40%) that lie on the $8 iso-utility line (see **Figure 4.2**). A specific color was then associated with each of these options. Because, these options are equal in utility, the rational account would suggest equal cuing effects for both options. Thus, in Experiment 5, a reward color x cue validity effect provides evidence against the rational homunculus.

### 4.7.1 Methods

Twenty-four participants (14 female) from the University of Iowa psychology research participant pool participated for partial course credit. The apparatus was identical to the one described in section **3.3.1 General Methods**.

*Stimuli and Design*

All participants completed a training and testing phase after successfully ( >80% accuracy) completing a short practice session. The experimental procedure is depicted in **Figure 4.4**. During all phases of the experiment, participants searched for a target letter (either X or Z) and responded with the appropriate keyboard button-press (either the “Z” key or the “?” key on a standard

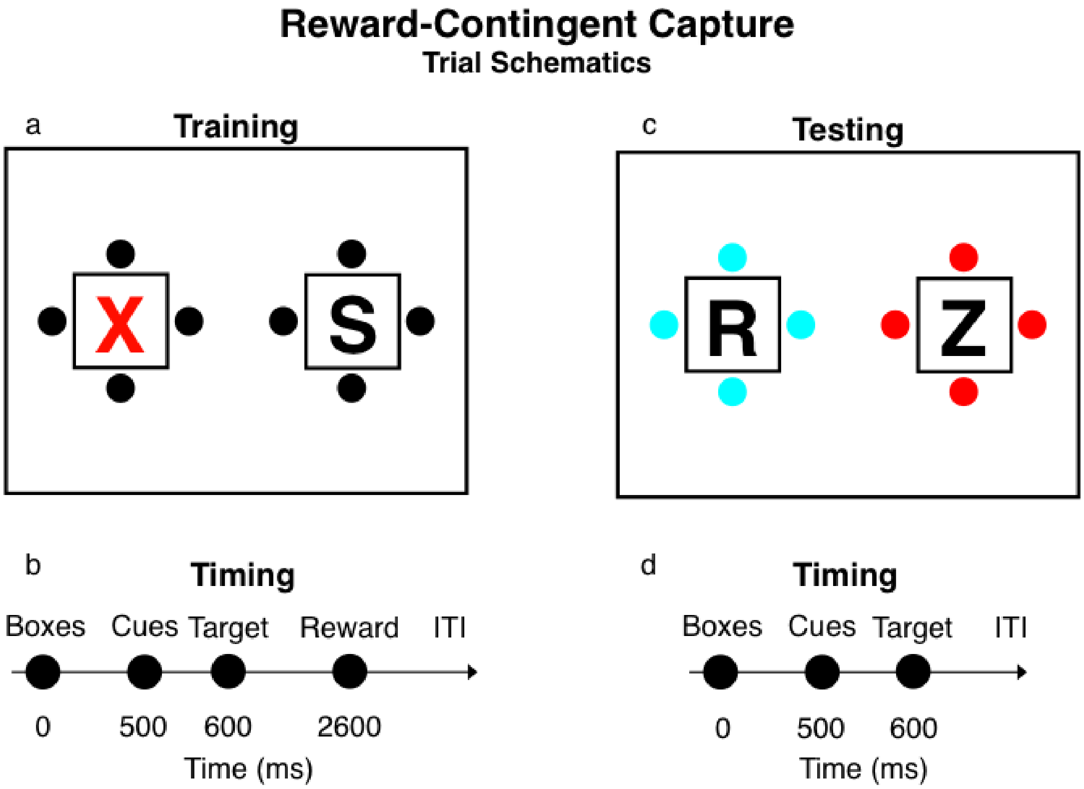

**Figure 4.4** *Reward contingent capture paradigm schematics.* The training phase (panels a and b) incorporated U.S. dollar bill stimuli as secondary reinforcers. Bills were associated with the color (red, blue, or green) of the target X or Z. The magnitude and the probability of reinforcement varied throughout Exps. 5-9. The testing phase (panels c and d) had a similar set-up to the training phase except that the colors were transferred from the letters to the cues. Novel and previously rewarded color cues appeared before the target. The previously rewarded colors could appear at the same (valid) or opposite (invalid) location of the target letter. Reward contingent capture is measured by taking the difference in RT between valid and invalid trials

keyboard layout). The letter stimuli subtended a visual angle of 1.5˚ wide and 2.0˚ tall. The target letter equally appeared in one of two white (RGB: 255, 255, 255) placeholder boxes spaced equidistant (5.0˚ visual angle) from the left and right of fixation. These placeholder boxes subtended a visual angle of 2.5˚ wide and 2.5˚ tall. A distractor letter (randomly drawn from the following pool: J, K, S, P, R, or V) appeared opposite the target. During the training phase only, the target letter appeared in one of three colors (red, RGB: 255, 0, 0; green, RGB: 0, 255, 0; or blue, RGB: 0, 0, 255) with equal frequency. At all other times, letters (targets and distractors) were drawn in white. Unbeknownst to the participant, the target color was associated with a specific schedule of reinforcement.

*Procedure*

During the training phase, and only ever after correct performance, participants viewed a rewarding image a U.S. bill. High-resolution bill stimuli (either \$10 or \$20 bill) were presented at the center of the screen and subtended a visual angle of 19.72˚ wide and 4.75˚ tall, which corresponds to the veridical dimensions of paper money. Three reinforcement schedules, one for each target color, were employed. Two colors were associated with an expected utility value of \$8 (see points **Figure 4.2**) and one color was never paired with reward. The colors associated with reward were equal in expected utility but were nonetheless differed along reinforcement magnitude and probability. One color, the probable-reward color, corresponded to an 80% likelihood of a \$10 bill image. The other rewarded color, the big-reward color, corresponded to a 40% chance of a \$20 bill image. Lastly, the neutral color was never associated with bill images. The colors for neutral, probable-, and big-reward were counterbalanced across participants.

Prior to the onset of the target, spatial cues appeared around the placeholder boxes. During practice and training, the cues were drawn in white, and served only to keep the presentation characteristics consistent across the phases. During the testing phase, the cues were drawn in one of six colors. For every trial in the testing phase, one cue was drawn in a reward-associated color seen during training (red, green, or blue) while the other cue was drawn in a novel color (yellow, RGB: 255, 255, 0; magenta, RGB: 255, 0, 255; or cyan, RGB: 0, 255, 255). The target was equally likely to appear at the location of the reward-associated cue and the location of the novel cue. The target was validly cued when a previously rewarded color cue appeared at the same location as the target and invalidly cued when a previously rewarded color cue appeared at the distractor letter's location. To track the rate of learning, and to strengthen acquisition, I repeated the train-test pairings three times (c.f., ABABAB design).

### 4.7.2 Results

*Training phase*

Mean RTs were computed on the basis of reward color (neutral, probable-reward, and big-reward). These data are graphed in **Figure 4.5**. Incorrect trials and response latencies ±2.5 SDs of

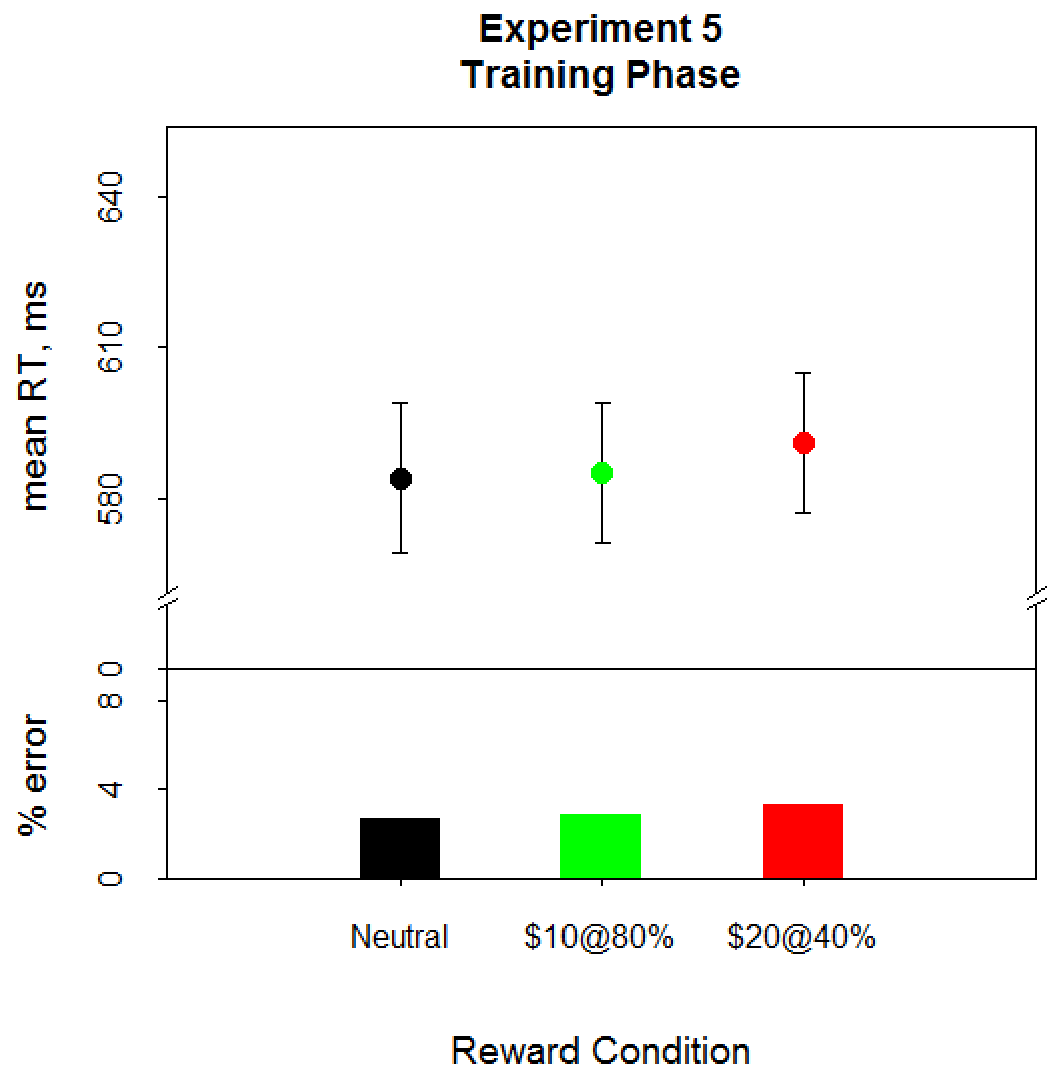

**Figure 4.5** *Experiment 5 training phase RT and error rates.* Error bars represent ±1 SEM

the mean were removed from analysis (this eliminated 8.0% of the data). A repeated-measures ANOVA revealed no significant RT effects in training, $F(2,46) = 1.25$, $p = .30$, $\eta_p^2 = .052$. Likewise, an analogous analysis of mean accuracy failed to reach significance, $F(2,46) = .68$, $p = .51$, $\eta_p^2 = .030$.

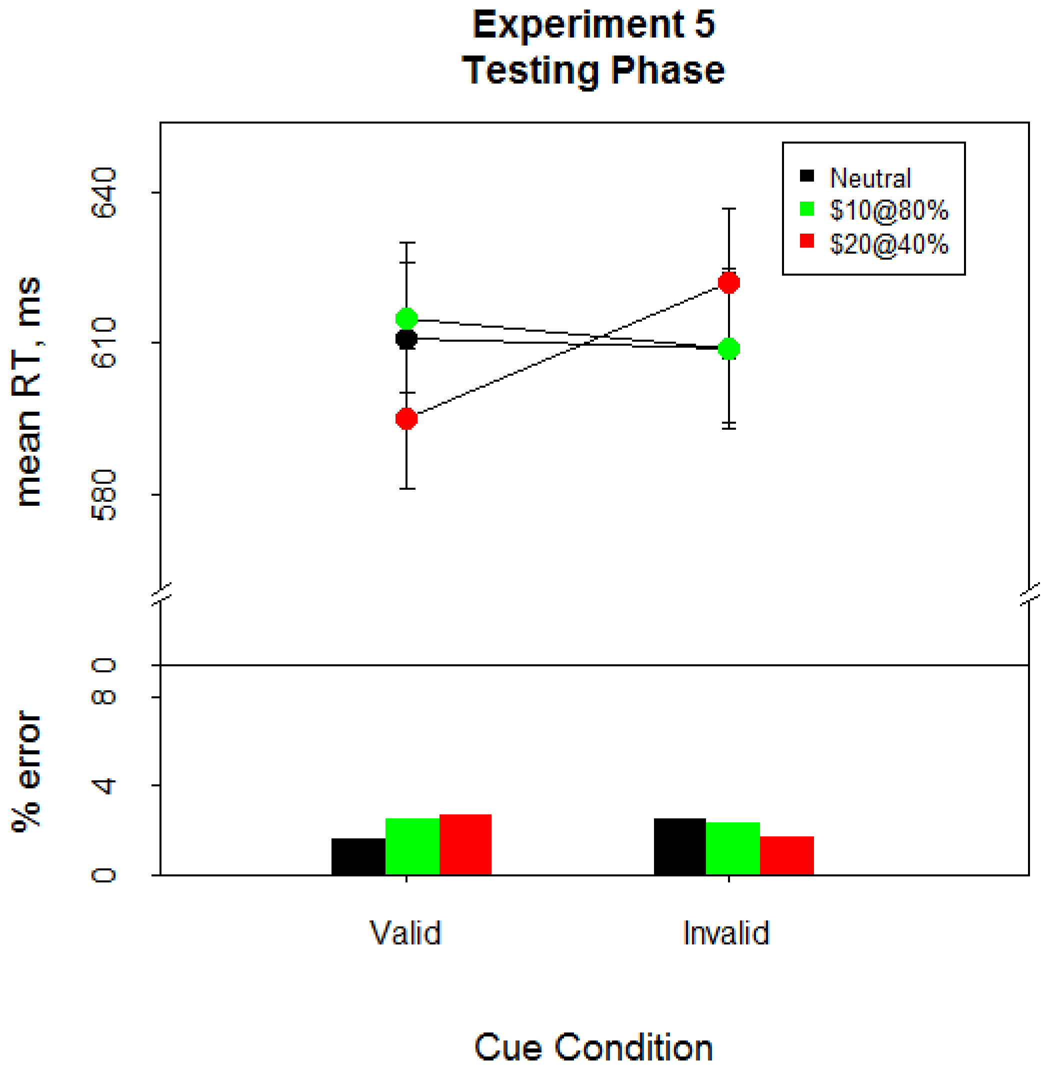

**Figure 4.6** *Experiment 5 testing phase RT and error rates.* Error bars represent ±1 SEM

### *Testing phase*

**Figure 4.6** plots mean RTs that were computed on the basis of reward color (neutral, probable-reward, and big-reward) and cue validity (valid or invalid). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 7.2% of the data). A repeated-measures ANOVA revealed a significant interaction between reward and validity, F(2,46) = 5.24, $p = .0090$, $\eta_p^2 = .19$. Follow-up analyses revealed a significant difference between valid and invalid trials for big-reward cues, $t(23) = 4.64$, $p < .001$, $\eta_p^2 = .70$, but not for probable-reward, $t(23) = .63$, $p = .53$, $\eta_p^2 = .13$, or neutral cues $t(23) = ..26$, $p = .80$, $\eta_p^2 = .05$. An analogous analysis of mean accuracy failed to reach significance, *p*s > .25.

### 4.7.3 Discussion

In Experiment 5, I observed RCC to the big-reward, but not the probable-reward color. This finding disconfirms a strict interpretation of the bean counter account and ultimately provides initial evidence that the attentional homunculus is an irrational economic actor. Apparently automatic attentional reward processes can appear rather intelligent. The results presented here embody converging evidence of Pavlovian conditioned attention in a new paradigm. Similar to the original value-driven attentional capture task, the RCC paradigm revealed attentional capture to a previously reward-associated color feature. This demonstrates that value-driven attentional priority serves to guide attention toward stimulus features that predict reward (and specifically that this can be done with images of money as secondary reinforcers, see **Chapter 3**, pg. 12). Most importantly, I observed an interaction that appears to falsify expected utility theory. The big-reward color produced greater cuing effects than the frequent-reward color. It could be said that the homunculus is risk-seeking at these values. It is however unclear how attention is differentially impacted by reward magnitude and reward probability.

## 4.8 EXPERIMENT 6: REWARD MAGNITUDE

In Experiment 5, I intentionally confounded rewarded probability and reward magnitude in order to provide a strong test of the bean counter account. In Experiment 6, I examined the independent contribution of reward magnitude difference by holding reward probability constant.

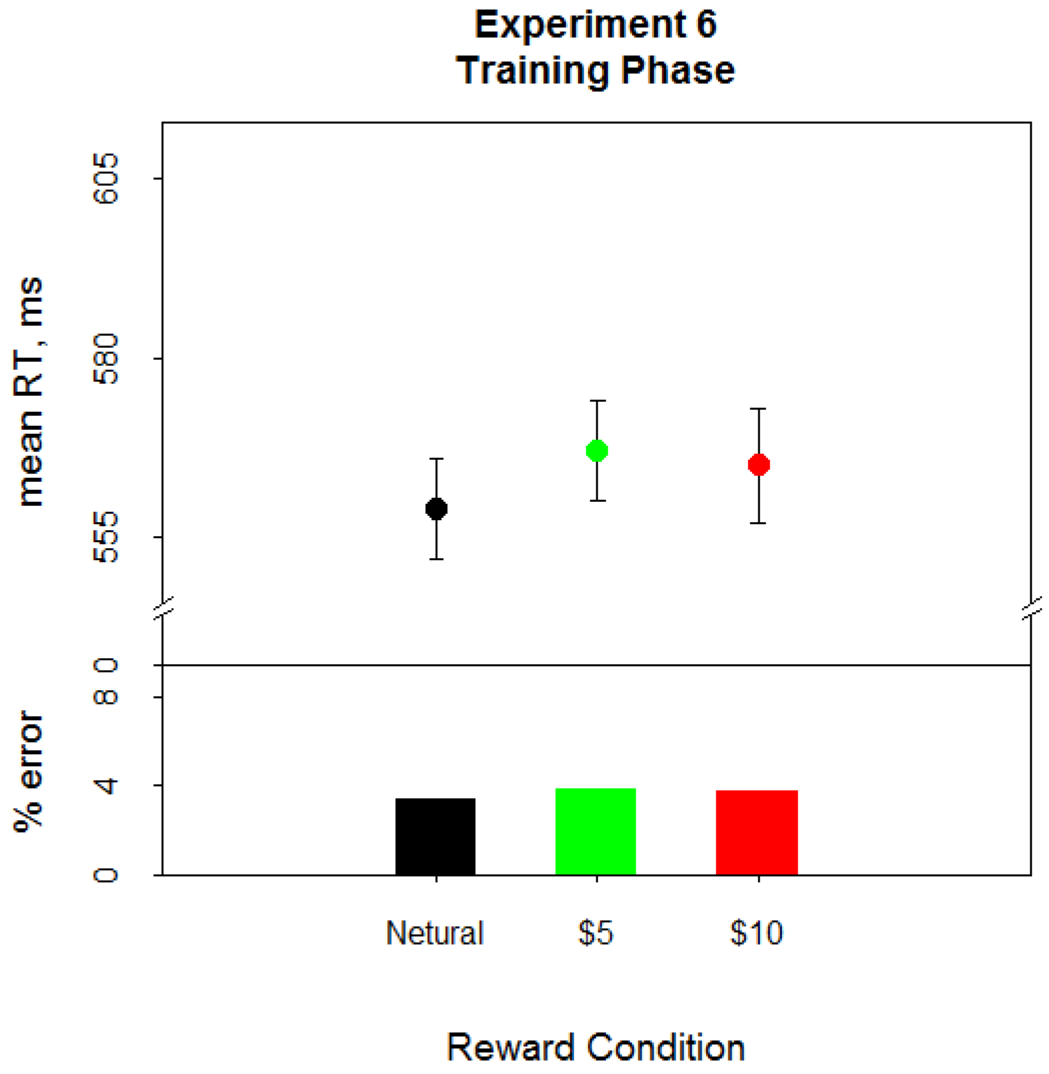

**Figure 4.7** *Experiment 6 training phase RT and error rates.* Error bars represent ±1 SEM

### 4.8.1 Method

*Participants*

Twenty-four participants (16 female) from the University of Iowa psychology research participant pool participated for partial course credit. All participants reported having normal or corrected-to-normal visual acuity and no color blindness. The University of Iowa Institutional Review Board approved the study and all participants provided informed consent.

*Stimuli and Design*

The task parameters for Experiment 6 were identical to Experiment 5 except for the schedules of reinforcement. During the training phase of Experiment 6, colors were associated with either no outcome, a low-value outcome (80% likelihood of $5), or a high-value outcome (80% likelihood of $10).

### 4.8.2 Results

*Training phase*

Mean RTs were computed on the basis of reward color (neutral, low-value, and high-value). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 7.1% of the data). These data are plotted in **Figure 4.7**. A repeated-measures ANOVA revealed no significant RT effects in training, $F(2,46) = 1.52$, $p = .23$, $\eta_p^2 = .062$. Likewise, an analogous analysis of mean accuracy failed to reach significance, $F(2,46) = .46$, $p = .64$, $\eta_p^2 = .019$.

*Testing phase*

**Figure 4.8** plots mean RTs that were computed on the basis of reward color (neutral, low-value, and high-value) and cue validity (valid or invalid). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 8.7% of the data). A repeated-

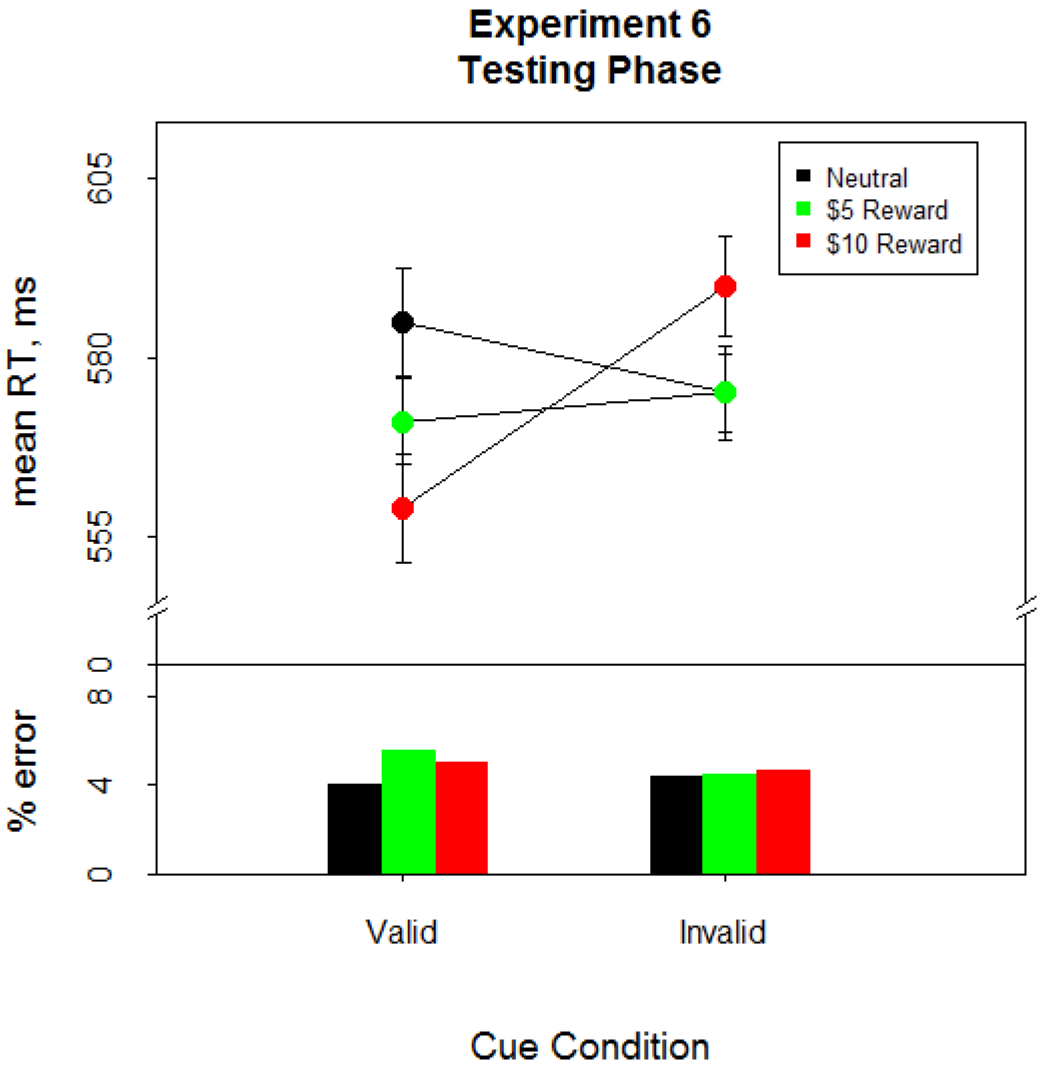

**Figure 4.8** *Experiment 6 testing phase RT and error rates.* Error bars represent ±1 SEM

measures ANOVA revealed a significant interaction between reward and validity, $F(2,46) = 5.37$, $p = .0080$, $\eta_p^2 = .19$. Follow-up analyses revealed a significant difference between valid and invalid trials for high-value cues, $t(23) = 3.74$, $p = .001$, $\eta_p^2 = .61$, but not for low-value, $t(23) = .49$, $p = .63$, $\eta_p^2 = .10$, or neutral cues $t(23) = .98$, $p = .34$, $\eta_p^2 = .20$. An analogous analysis of mean accuracy failed to reach significance, *p*s > .33.

### 4.8.3 Discussion

When I varied reward magnitude while holding reward probability constant, I found greater RCC to the color associated with higher rewards. This finding is a built in replication to Experiment 5 and therefore helps validate the RCC task, but it does not further disambiguate the homunculus' economic behavior. Next I examined reward probability while holding reward magnitude constant.

## 4.9 EXPERIMENT 7: REWARD PROBABILITY

### 4.9.1 Method

*Participants*

Twenty-four participants (16 female) from the University of Iowa psychology research participant pool participated for partial course credit. All participants reported having normal or corrected-to-normal visual acuity and no color blindness.

*Stimuli and Design*

The task parameters for Experiment 7 were identical to Experiment 5 except for the schedules of reinforcement. During the training phase of Experiment 7, colors were associated with either no outcome, a low-value outcome (40% likelihood of $10), or a high-value outcome (80% likelihood of $10).

### 4.9.2 Results

*Training phase*

Mean RTs were computed on the basis of reward color (neutral, low, and high-value). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 10.4% of the data). These data are depicted in **Figure 4.9**. A repeated-measures ANOVA revealed no significant RT effects in training, $F(2,46) = 1.81$, $p = .18$, $\eta_p^2 = .073$.

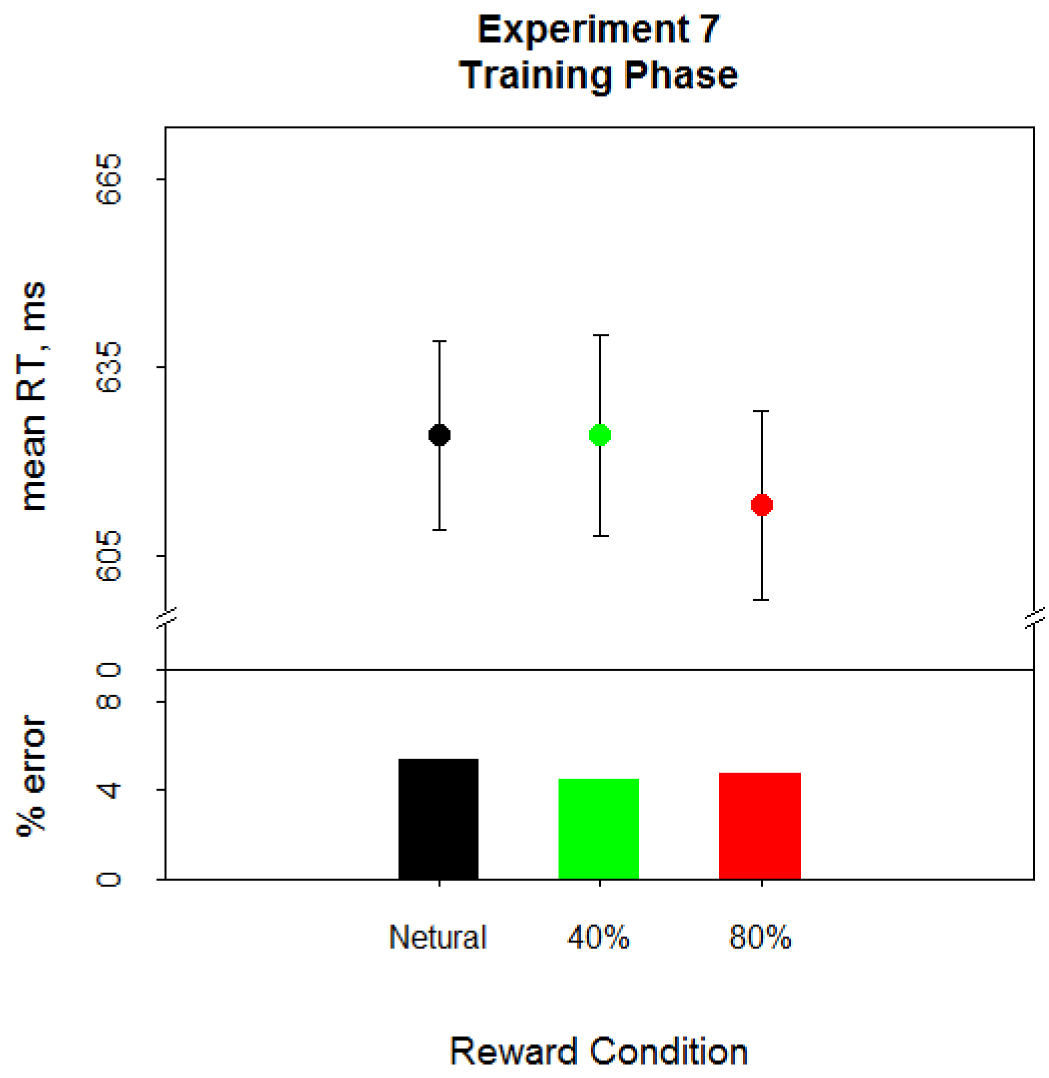

**Figure 4.9** *Experiment 7 training phase RT and error rates.* Error bars represent ±1 SEM

Likewise, an analogous analysis of mean accuracy failed to reach significance, $F(2,46) = .88$, $p = .42$, $\eta_p^2 = .037$.

*Testing phase*

**Figure 4.10** plots mean RTs that were computed on the basis of reward color (neutral, low, and high value) and cue validity (valid or invalid). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 10.3% of the data). A repeated-measures

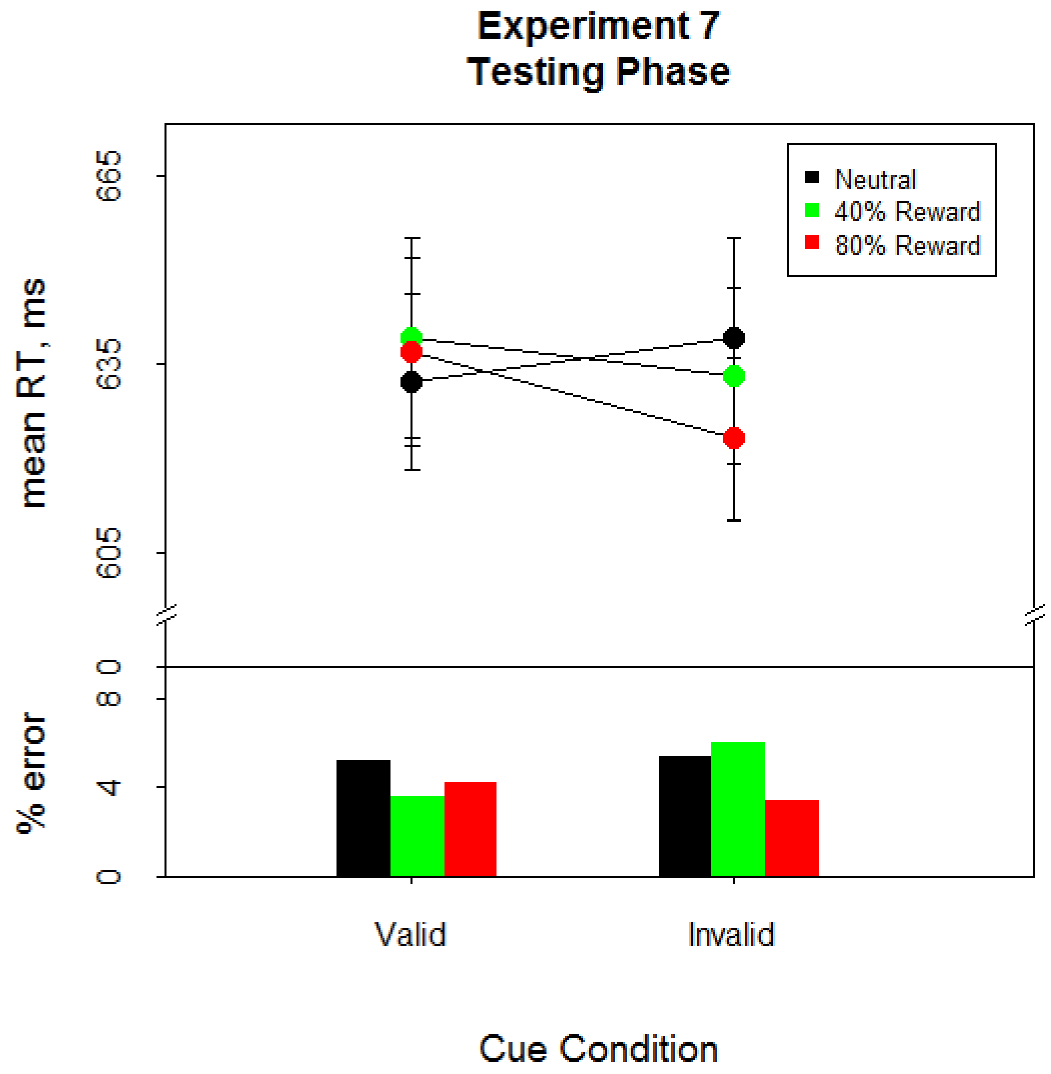

**Figure 4.10** *Experiment 7 testing phase RT and error rates.* Error bars represent ±1 SEM

ANOVA revealed no significant RT effect in testing, *p*s ≥ .41, $\eta_p^2$s ≤ .037. An analogous analysis of mean accuracy revealed a significant main effect of reward, *F*(2,46) = 4.33, *p* = .019, $\eta_p^2 = .16$. Follow-up analyses revealed accuracy for high-value trials was greater than accuracy for neutral trials, *t*(23) = 2.17, *p* = .040, $\eta_p^2 = .41$. The contrast between low-value trials and the other two conditions was not significant, *p*s > .18. There was also a significant reward x validity interaction, *F*(2,46) = 3.24, *p* = .048, $\eta_p^2 = .12$. Follow-up analyses revealed a significant difference between valid and invalid trials for low-value cues, $t(23) = 3.01$, $p = .006$, $\eta_p^2 = .53$, but not for high-value, $t(23) = 1.07$, $p = .30$, $\eta_p^2 = .22$, or neutral cues $t(23) = .23$, $p = .81$, $\eta_p^2 = .05$.

### 4.9.3 Discussion

When colors differed in reward probability alone, I observed no differential RCC effect in RT. In Experiment 6, I observed a significant difference in RCC at a 2x magnitude factor. In contrast, in Experiment 7, I failed to observe RCC differences at a 2x probability factor. This suggests that the probability dimension is less highly weighted.[2] In the limit, the attentional system must logically consider reward probability when assigning attentional weights (i.e., a 100% probability differential between two options is the same as the high-value vs. reward-neutral contrast). Therefore, it is likely that a larger probability difference is required to observe differential effects of attentional processing. Therefore, I conducted Experiment 8 that incorporates a 4x probability differential.

## 4.10 EXPERIMENT 8: EXTREME TEST OF REWARD PROBABILITY

### 4.10.1 Methods

*Participants*

Twenty-four participants (16 female) from the University of Iowa psychology research participant pool participated for partial course credit.

*Stimuli and Design*

The task parameters for Experiment 8 were identical to Experiment 5 except for the schedules of reinforcement. During the training phase of Experiment 8, colors were associated

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[2] Although I also recognize that with sufficient training, the attentional system may become sensitive to a 2x probability factor.

with either no outcome, a low-value outcome (20% likelihood of $20), or a high-value outcome (80% likelihood of $20).

### 4.10.2 Results

*Training phase*

Mean RTs were computed on the basis of reward color (neutral, low, and high value). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 10.3% of the data). These data are illustrated in **Figure 4.11**. A repeated-measures

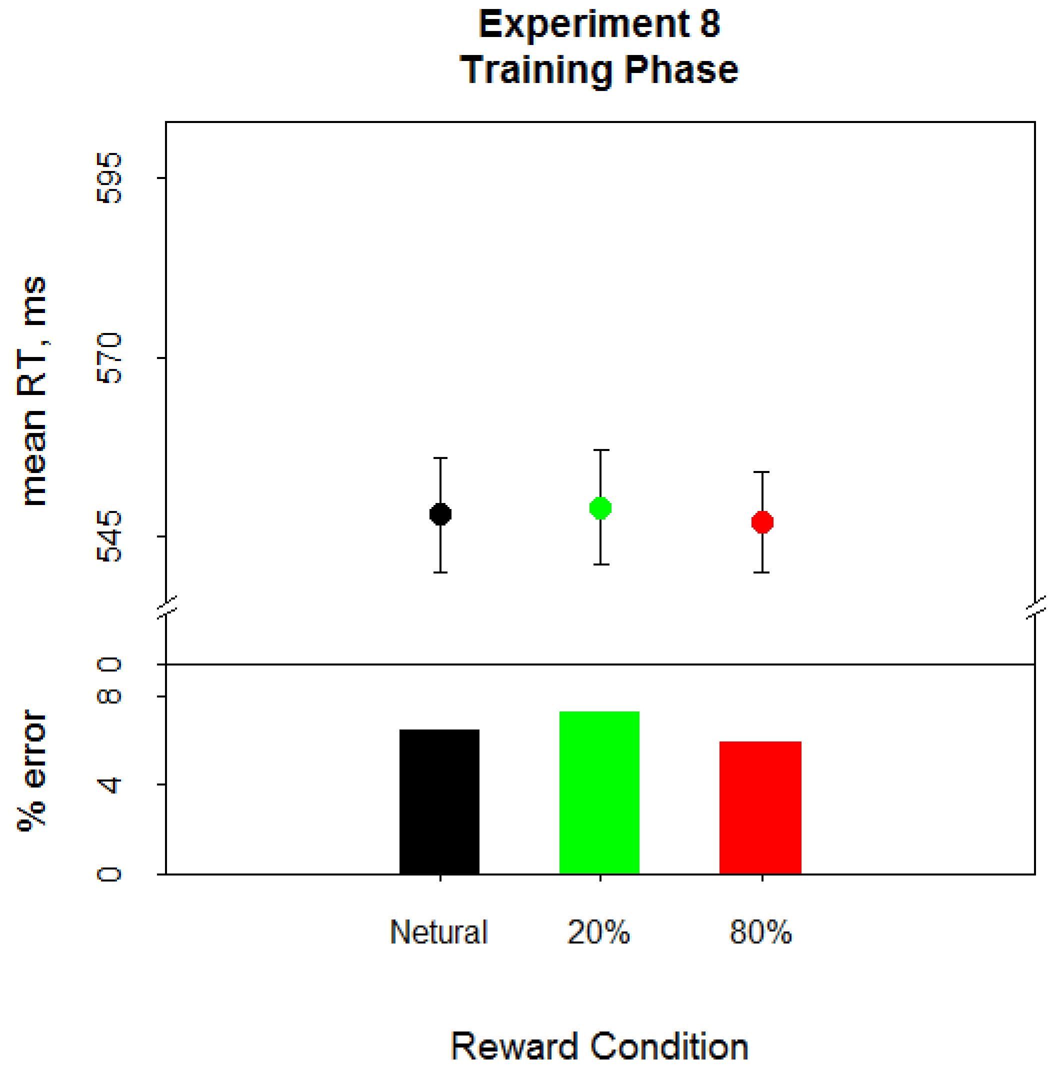

**Figure 4.11** *Experiment 8 training phase RT and error rates.* Error bars represent ±1 SEM

ANOVA revealed no significant RT effects in training, $F(2,46) = .066$, $p = .94$, $\eta_p^2 = .0030$. Likewise, an analogous analysis of mean accuracy failed to reach significance, F(2,46) = 2.55, $p = .089$, $\eta_p^2 = .10$.

*Testing phase*

**Figure 4.12** plots mean RTs that were computed on the basis of reward color (neutral, low, and high value) and cue validity (valid or invalid). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 11.1% of the data). A repeated-measures ANOVA revealed a significant interaction between reward and validity, F(2,46) = 3.22, $p = .049$, $\eta_p^2 = 12$. Follow-up analyses revealed a significant difference between valid and invalid trials for high-value cues, $t(23) = 2.70$, $p = .013$, $\eta_p^2 = .49$, but not for low-value, $t(23) = .11$, $p = .92$, $\eta_p^2 = .02$, or neutral cues $t(23) = .40$, $p = .69$, $\eta_p^2 = .08$. An analogous analysis of mean accuracy failed to reach significance, $p\text{s} \geq .37$, $\eta_p^2\text{s} \leq .043$.

### 4.10.3 Discussion

In Experiment 8, I found an effect of reward probability at a 4x ratio. The color associated with an 80% probability of $20 produced greater RCC than did the color associated with a 20% probability of $20. Therefore, attention is apparently sensitive to reward probability, however, reward magnitude is a more effective contributor at the 2x factor. The RCC effect size due to a 2x magnitude factor in Experiment 6 is equivalent to the RCC effect size due to a 4x probability factor in Experiment 8. Therefore there appears to be a psychological underweighting of the probability dimension as a whole. This is similar to other findings in the literature (Stauffer et al., 2015).

The results of Experiments 5-8 demonstrate clear value effects on attention. Reward magnitude and to a lesser extent reward probability each play a role in the allocation of spatial attention. Lastly, in Experiment 9, I reexamine the attentional homunculus question after controlling for the psychological underweighting of reward probability.

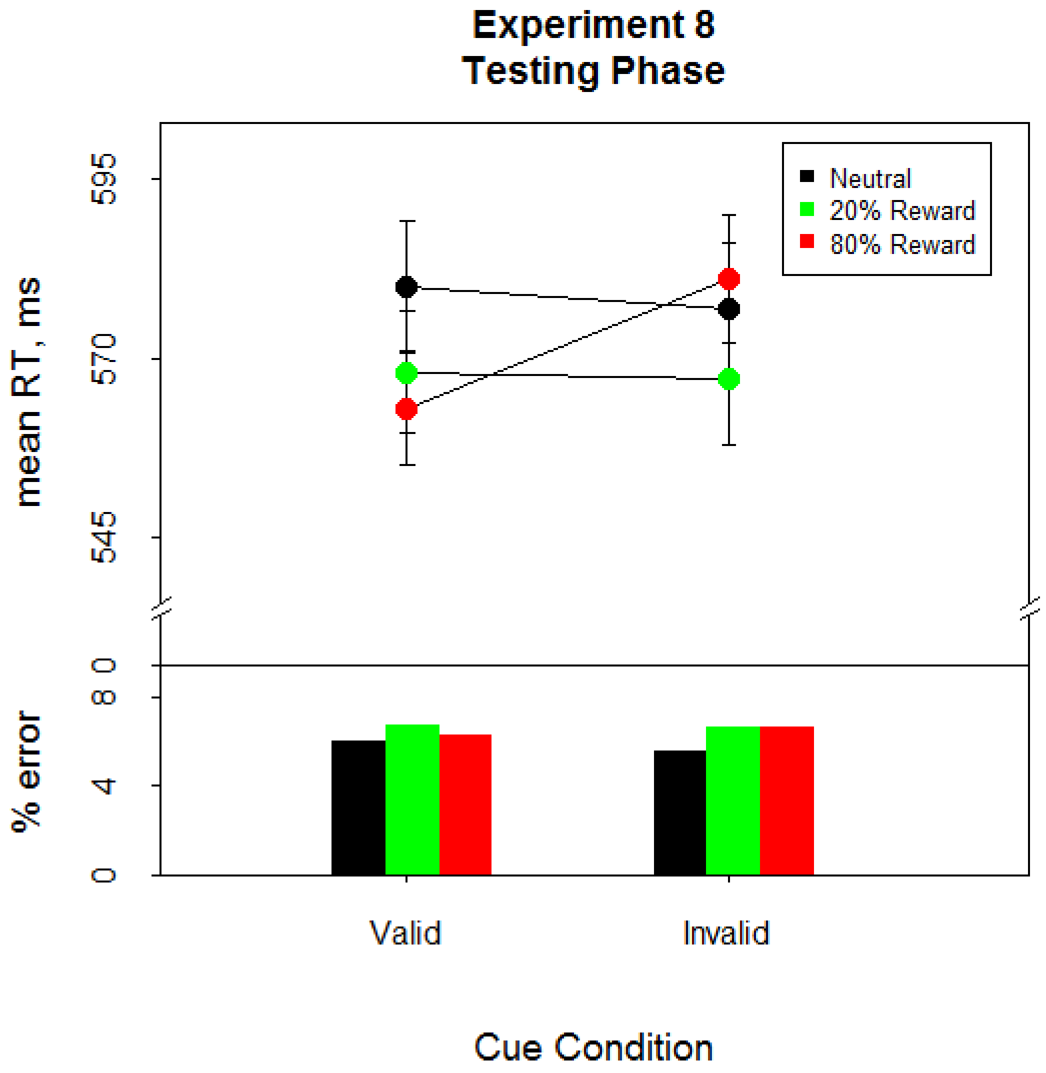

**Figure 4.12** *Experiment 8 testing phase RT and error rates.* Error bars represent ±1 SEM

## 4.11 EXPERIMENT 9: EXPECTED VALUE REVISITED

Lastly, I revisit expected value with a renewed perspective. With the proper psychological correction for probability underweighting, I again crossed reward magnitude against reward probability. Despite the expected utility gradient between the big-reward and the probable-reward, here I expected no reward by validity interaction because the available rewarded options are psychologically equivalent.

### 4.11.1 Method

*Participants*

Twenty-four participants (12 female) from the University of Iowa psychology research participant pool participated for partial course credit.

*Stimuli and Design*

The task parameters for Experiment 9 were identical to Experiment 5 except for the schedules of reinforcement. During the training phase of Experiment 9, colors were associated with either no reward, a probable-reward (80% likelihood of $10), or a big-reward (20% likelihood of $20).

### 4.11.2 Results

*Training phase*

Mean RTs were computed on the basis of reward color (neutral, low, and high value). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 10.3% of the data). These data are depicted in **Figure 4.13**. A repeated-measures

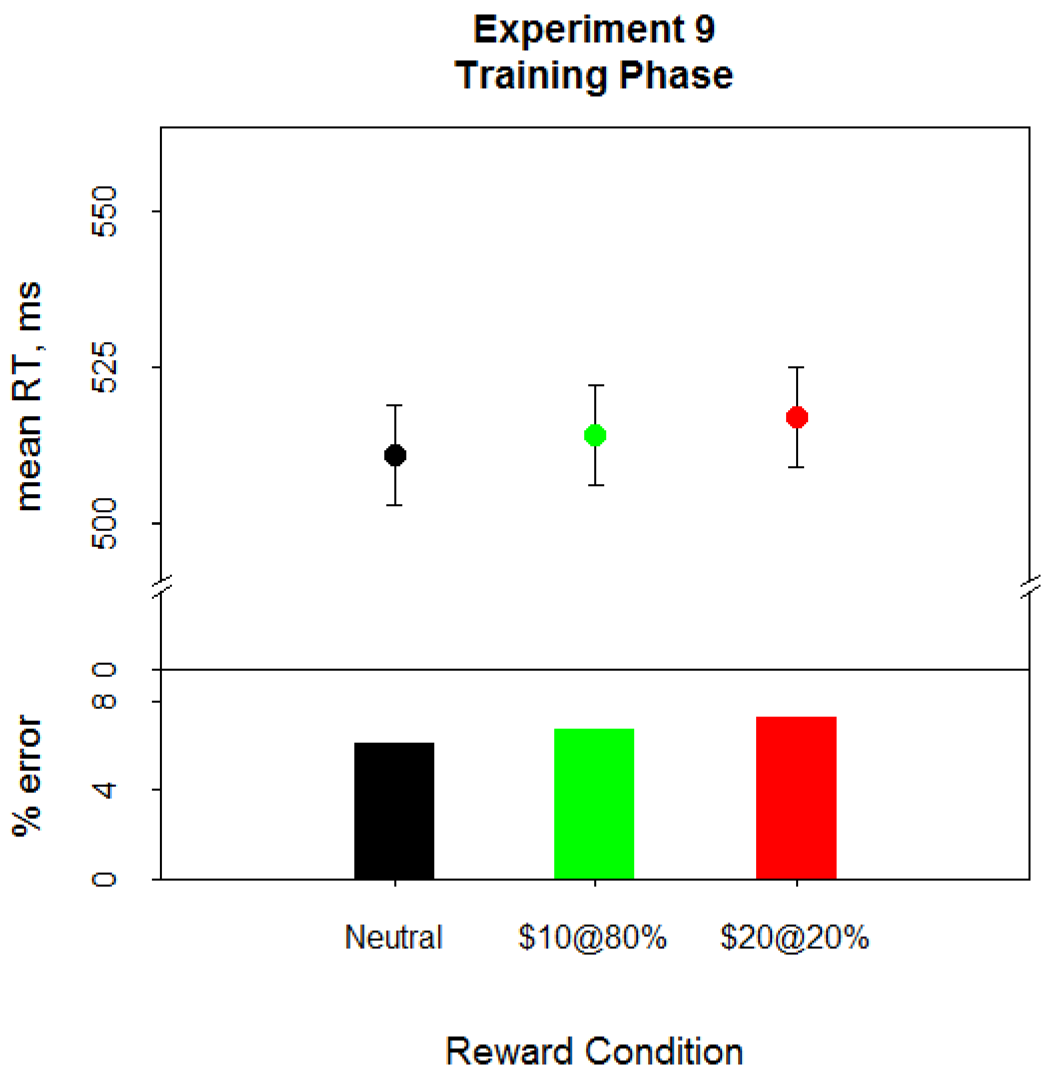

**Figure 4.13** *Experiment 9 training phase RT and error rates.* Error bars represent ±1 SEM

ANOVA revealed no significant RT effects in training, F(2,46) = 1.33, $p$ = .28, $\eta_p^2$ = .055. Likewise, an analogous analysis of mean accuracy failed to reach significance, F(2,46) = .60, $p$ = .56, $\eta_p^2$ = .025.

*Testing phase*

**Figure 4.14** plots mean RTs that were computed on the basis of reward color (neutral, low, and high value) and cue validity (valid or invalid). Incorrect trials and response latencies ±2.5 SDs

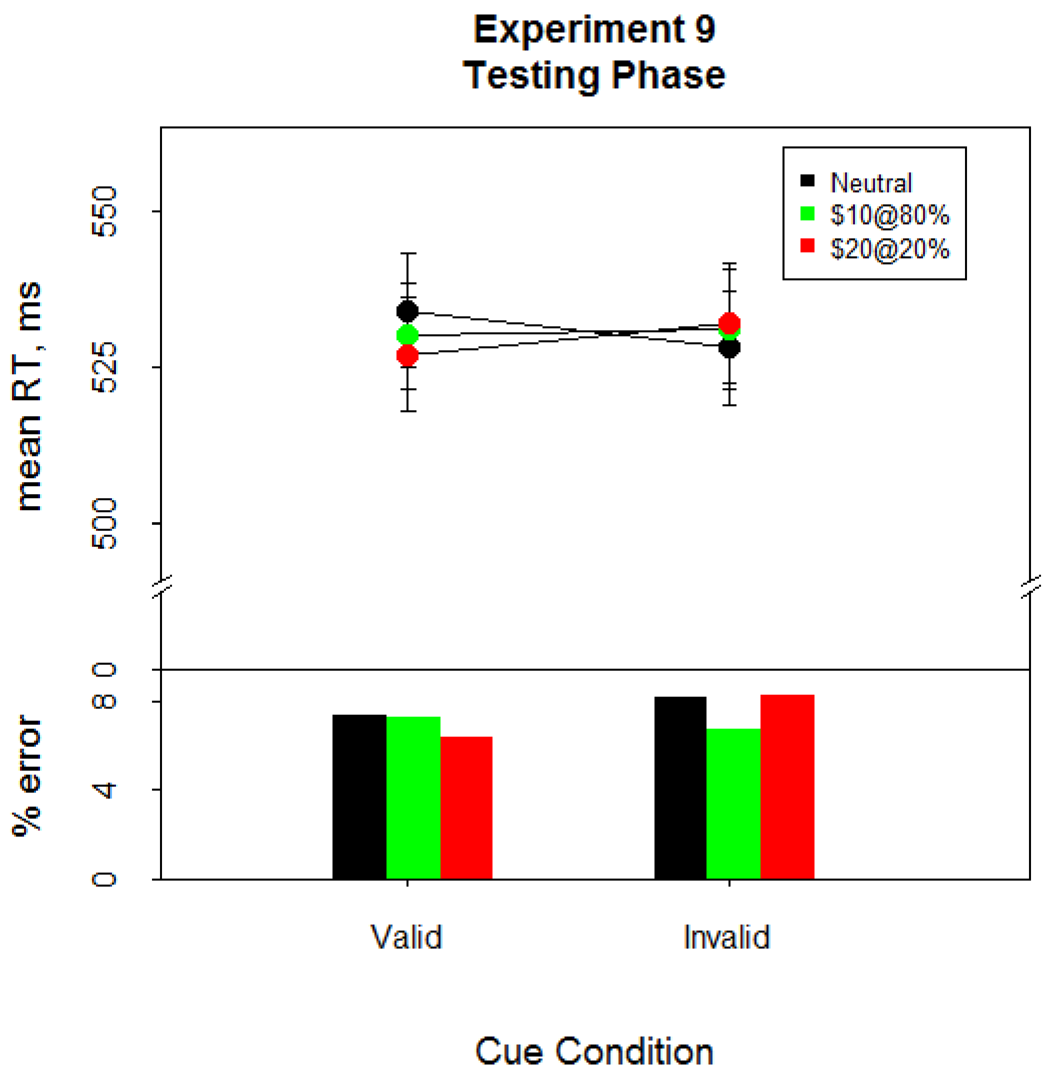

**Figure 4.14** *Experiment 9 testing phase RT and error rates.* Error bars represent ±1 SEM

of the mean were removed from analysis (this eliminated 10.9% of the data). A repeated-measures ANOVA revealed no significant RT effect in testing, *p*s $\geq$ .45, $\eta_p^2$s $\leq$ .034. An analogous analysis of mean accuracy failed to reach significance, *p*s $\geq$ .26, $\eta_p^2$s $\leq$ .057.

### 4.11.3 Discussion

After correcting for psychological underweighting of reward probability, I found no difference between a clearly larger reward and a smaller reward. Although I observed null effects in Experiment 9, the null results were predicted based on Experiments 5-8. It is important to consider how the results of Experiment 5 compare to Experiment 9. The only difference between the Experiments 5 and 9 is that the big-reward in Experiment 9 was presented with a 20% probability rather than 40% in Experiment 5. This shift served only to reduce attention to the big-reward color and it did nothing to boost the salience of the probable-reward color. Indeed, after shifting down the probability of the big-reward, I no longer observed RCC for the big-reward color.

## 4.12 CHAPTER SUMMARY

Apparently, the attentional homunculus is not a rational economic actor. In Experiments 5-9, I demonstrated three clear violations of the expected value hypothesis. In Experiment 5, I found an effect where, according to expected value, there should not have been. In Experiments 7 and 9, I found no effect where the expected value hypothesis would have predicted effects. It is important to note that these null effects were not due to a lack of power as all 5 experiments had 24 data-sets. Together these results provide disconfirmatory evidence for the economically rational attentional homunculus.

In the RCC task, participants were told to search for a target letter that incidentally appeared in one of three colors. This differs from the existing value-driven attentional capture task. Whereas in the original task participants searched for a red/green ring, in the new task, color was irrelevant, but nonetheless reward-predictive. Thus as stipulated by goal-directed attention, participants were not motivated to hold explicit target templates for the rewarded features. This novel finding sets RCC apart from regular contingent capture because in the contingent capture paradigm participants have an explicit goal to search for the distractor color.

By introducing discontinuity between training and testing, I observed that value-driven attentional priority generalized to the irrelevant feature dimension of color. The adapted task had distractors during the testing phase that shared color but not shape with the rewarded stimuli. This discontinuity tested whether value-driven attentional priority extends to stimuli that share only color with the target (c.f. Anderson, Laurent, & Yantis, 2012). I observed greater capture to the previously high rewarded color than to low reward and neutral colors. This finding demonstrates that value-driven attentional priority can generalize to stimuli across a feature dimension (e.g., red Xs prioritized red circles).

The current work provides converging evidence that reward probability is processed non-linearly in the brain. Prospect theory demonstrates how high-level economic decisions are influenced by the very same probability distortions (von Neumann & Morgenstern, 2007). The experiments presented is **Chapter 4** provide a complementary account by demonstrating how probability distortions emerge from experience with stimuli associated with varying payoffs. Likewise, similar distortions have been shown under more controlled paradigms in the primate model (Stauffer et al., 2015).

# 5 SHAPED TO SEARCH: EXTENDING VALUE LEARNING TO HIGHER ORDER COGNITIVE FUNCTIONS

In **Chapters 3** and **4**, I demonstrated how colors can be classically conditioned to produce lingering attentional biases. These forms of feature-specific rewarded attention effects exert powerful control over behavior. However, to fully account for higher-order human behavior one has to show that rewarded attention can operate on likewise higher-order and feature-unspecific processes. For instance, TSA baggage screening requires effortful visual search (Biggs et al., 2013). Screeners must be able to separate contraband from the clutter under demanding time pressure. This task is often accomplished without a rigid target template, that is screeners do not know the specifics of what they are searching for only that they are searching for objects that meet a certain category (e.g., blade-shaped or gun-shaped). Feature-specific attentional mechanisms cannot readily account for such higher-order, strategic behavior. To date, few studies have explored the role of rewards on such global attentional strategies (but see Kawahara, 2010). Thus, there is an empirical gap in the rewarded attention literature that disconnects it from the everyday life experience of strategic attentional deployment. In **Chapter 5**, I address how rewards can be implemented to tune attentional set behavior.

## 5.1 THE ATTENTIONAL SET

The *attentional set* is a construct designed to represent the preparatory state of action taken by attention to prioritize the selection of simple visual features. For example, attention can be set for the color red and consequently red objects are prioritized. This process takes effort and requires the strategic allocation of attentional resources – a rather extraordinary feat. It is under these premises that I characterize the cognitive process of adopting a specific attentional set as a covert behavior. We know that overt behaviors are readily shaped by rewards (see **Chapter 3**), however, it is unknown to what extent reinforcement learning principles apply to high-order cognitive behavior such as those involved in establishing the attentional set. Below, I describe the behavior of the attentional set in terms of two distinct attentional search modes. Later, I show how rewards could be integrated to bias the adoption of specific search modes.

### 5.1.1 Singleton Detection Mode

When conducting a visual search, humans can adopt at least two different attentional sets: singleton detection mode and feature search mode. S*ingleton detection mode* is a diffuse attentional set where priority is assigned to the most salient item in the visual field (Pashler, 1988). In singleton detection mode, participants do not hold a specific template in mind but instead search for the oddball item. Consequently, salient but task-irrelevant color distractors capture attention because they abstractly fit the target description (i.e., being an oddball). It is important to note that singleton detection mode is indifferent to feature dimension. That is, when participants search for a shape pop-out target, singleton color distractors capture attention. Theeuwes (1992) introduced the additional singleton paradigm in which participants are forced into singleton detection mode. In this task, participants conduct a visual search for a shape singleton. Specifically, they search for a circle amongst diamonds or a diamond amongst circles. They could not predict whether the target of an upcoming trial would be either of the two shapes and thus they should adopt the strategy to simply search for the odd shape. On half of the trials, a color singleton is present within the display. The typical finding is that RT is longer to identify the target when the distractor is present versus absent. This is an example of stimulus-driven capture which demonstrates that attentional priority can be set on the general basis of display heterogeneity.

### 5.1.2 Feature Search Mode

In contrast, when in *feature search mode*, participants maintain a narrow attentional set (Bacon & Egeth, 1994). This narrow set filters stimuli on the basis of the target's perceptual characteristics (Folk et al., 1992; Leber & Egeth, 2006). Given the proper stimulus environment, a participant set in feature search mode for a red target, will be captured by a red, but not a green distractor (Folk, Leber, & Egeth, 2002). Therefore, when in feature search mode, participants are robust to distraction unless the distractor in some way shares the features of the current target template. Feature search mode, however, is a laborious, effort-consuming strategy. Bacon and Egeth (1994) argue that it is less effortful to adopt singleton detection mode because a rigid template does not need to be maintained. Putatively, the attentional system tolerates some distraction in exchange for minimal energy expenditure. Therefore, energy wise, it is an optimal strategy to adopt singleton detection mode. In contrast however, in cluttered environments (e.g., baggage screening) when multiple salient objects are present, singleton search mode can be as ineffective as random search. Thus, feature search mode might require effort, but it is nevertheless optimal for search in cluttered environments where simple feature differences get lost in the noise.

In order to adopt feature search mode, observers must form a search template. However, there are several ways for templates to be established. A participant can form a template based on the experimenters' instructions (e.g., "Search for a red circle."). The immediate stimulus environment can affect the template (Wolfe & Horowitz, 2004) and the prolonged use of an attentional set primes subsequent use of that same set (Cosman & Vecera, 2014; Leber & Egeth, 2006a, 2006b). For example, Leber and colleagues (2006a) trained one group of participants to use singleton detection mode and another group to use feature search mode. Following training, they gave all participants a series of option trials where either search mode could be implemented.

The researchers found that when given the option, participants will persist with the most recently used strategy. They concluded that the attentional system perseverates (operates on “auto-pilot”) when choosing a search mode. This conclusion converges with models of executive control (Norman & Shallice, 1986) and supports the view that attentional search modes represent higher-order cognitive function.

## 5.2 EXPERIMENT 10: SHAPED SEARCH MODES

The outline above identifies the attentional set as a covert attentional strategy. I posited that as a behavior able to be shaped by experience, the attentional set should also respond to rewards. In Experiment 10, I trained three groups of participants to perform visual search over an intermixed display set. Half of the displays were homogeneous distractor searches where the target was a shape singleton, for the other half, the target was always a circle embedded in a heterogeneous array of distractor shapes. Thus for some displays, singleton detection mode was the optimal strategy and for other displays feature search mode was optimal. Critically, all participants were exposed to the same number of displays from each category. The only difference between the groups was the association of the displays to specific rewarding outcomes. One group was trained to value feature search – a high-value bill (U.S. $20) image appeared after heterogeneous distractor displays and a low-value bill ($1) image appeared after homogeneous distractor displays. A second group was trained to value singleton detection mode – a high-value bill appeared after a homogeneous distractor display and a low-value bill appeared after a heterogeneous display. A third group performed the same procedure as the previous groups except that the bill stimuli were replaced with generic accuracy feedback. This control group provided a measure of the natural or default attentional set behavior under the same experimental conditions as the rewarded groups.

Subsequent to training, participants completed an option search where they could choose to adopt a diffuse (singleton mode) or narrow (feature search) search strategy. I hypothesized participants would use the attentional set that was previously highly rewarded in the training session. During the option search phase, a salient color distractor appeared on half the trials. The amount of attentional capture to this color distractor can be used to infer which search mode participants employed. Specifically, large attentional capture effects indicate the use of singleton detection mode, whereas the absence of capture effects indicates the use of feature search mode (compare **Chapter 5.2**). Based on the reinforcement schedules employed during training, I predicted greater attentional capture in the value-singleton group than the value-feature group.

In **Chapters 3** and **4**, I demonstrated that images of U.S. dollar bills can act as powerful secondary reinforcers. In those previous studies bill images were associated with specific low-level stimulus features, like the color red. In contrast, the experiments reported in the following sections will use bill images as reward to influence higher-order and stimulus-unspecific search modes. I found that implicit rewards can flexibly shape attentional set behavior by throttling cognitive control mechanisms.

### 5.2.1 General Methods

#### *Participants*

Thirty-six participants (23 female) participated for course credit. See **3.3.1 General Methods** for details about the experimental set-up.

#### *Stimuli and Design*

The experiment involved a training phase with rewards and a testing phase with a critical distractor. The experiment consisted of six alternating train-test blocks of 72 trials each (i.e.,

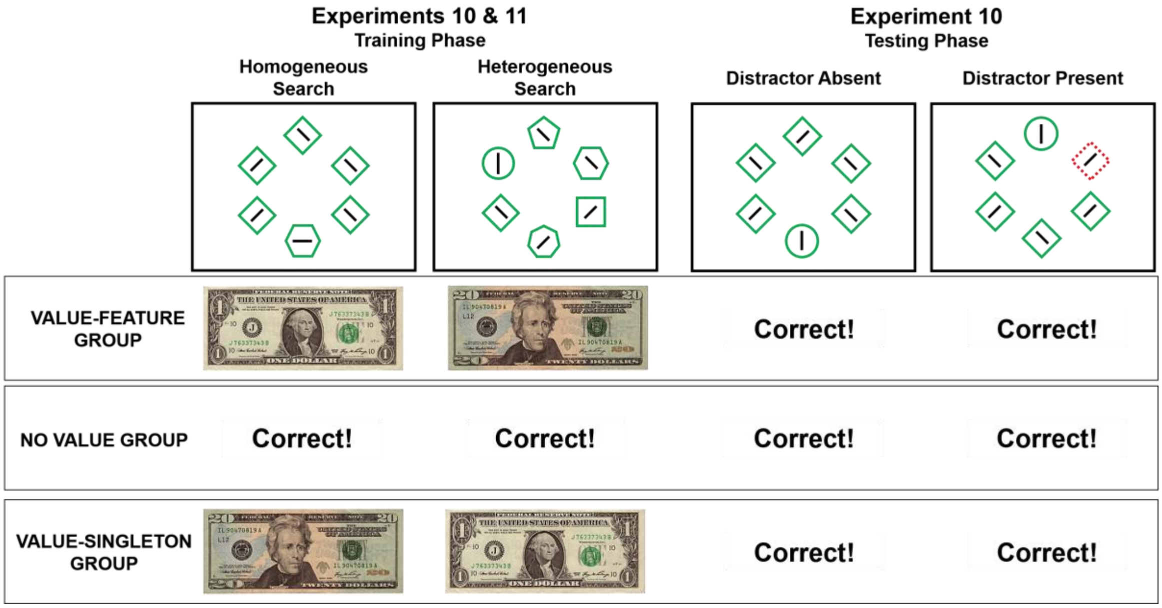

**Figure 5.1** *Training and testing phase schematics*. Search displays were differentially reinforced between two groups and a third group was never exposed to bills. The figure depicts the reward pairing for each group. In the training phase, the target (vertical/horizontal line) appeared either in a circle (heterogeneous search displays) or a shape singleton (homogeneous search displays). The testing phase was identical for all three groups. Participants searched for a target line within a circle (Exp. 10) or a square (Exp. 11 & Exp. 12). The dashed line depicts a task-irrelevant color singleton distractor that was present on 50% of the testing trials. In the actual experiments, the background was dark gray

ABABAB design). Stimulus displays for the two phases are illustrated in **Figure 5.1**. Training consisted of two types of trials – heterogeneous search displays and homogeneous search displays. An equal number of these displays were randomly intermixed within each training block. Participants searched for a black line segment on a dark gray background. The line segment was contained within a shape (circle, diamond, hexagon, square, pentagon, or heptagon) and participants were instructed to report its orientation (vertical or horizontal). Six shapes were presented on every trial. On homogeneous search trials, the target always appeared within a unique shape (e.g., diamond amongst squares). On heterogeneous search trials, the target was always inside a circle and the remaining shapes were varied.

During the training phase only, images of U.S. dollar bills appeared after correct trial performance. Twelve participants, hereafter referred to as the value-singleton group, were highly rewarded (100% chance of a $20 bill) after singleton search trials and lowly rewarded (100% chance of a $1 bill) after heterogeneous search trials. This contingency was reversed for a second set of twelve participants, hereafter referred to as the value-feature group. A third set of twelve participants, the no-value group, was never rewarded. Critically, all participants knew in advance they were to receive a fixed amount of course credit and *zero* monetary payment as compensation.

The testing phase was identical to the singleton search condition of the training phase except that the target was always a circle and a single non-target shape occasionally appeared (in 50% of trials) as a uniquely colored distractor (e.g., red square amongst yellow squares and yellow circle). This color singleton was poised to distract attention away from the target via stimulus-driven attentional capture (not value-driven attentional capture). Prior to the experiment, all participants were randomly assigned one of three base colors (red, RGB: [255 0 0], green, [0 255 0], or yellow, [255 255 0]). All stimuli, except for the distractor in the testing phase, were rendered in the specific base color assigned to each participant. The distractor's color was randomly chosen from the two remaining colors. In Experiments 10 and 11, the base and distractor colors were consistent throughout the task.

Participants engaged in singleton search mode should be non-specifically looking for the different item and thus be particularly prone to salient distractors. However, participants engaged in feature search mode should be looking for a specific shape (circle) and thus be configured to easily avoid color-induced distraction. Therefore, I hypothesized that if rewards bias attentional set behavior, then participants in the value-singleton group should show evidence of greater distraction than the value-feature group.

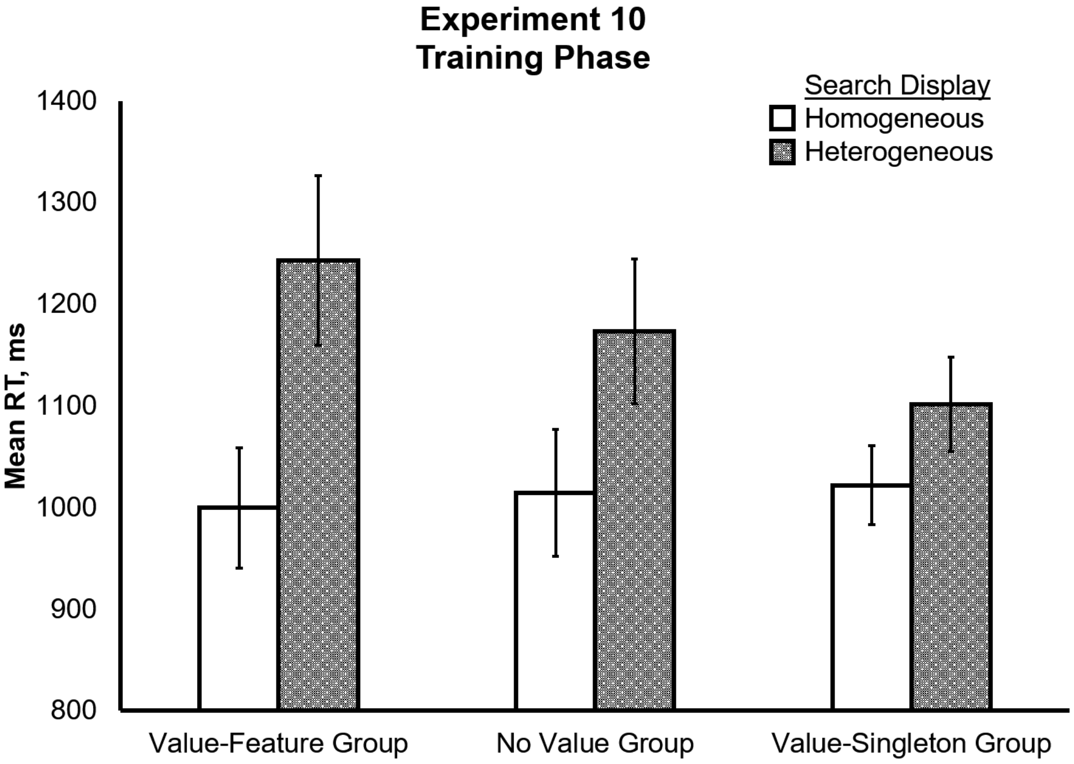

**Figure 5.2** *Experiment 10 training phase RT.* Errors bars represent ±1 SEM

### 5.2.2 Results

*Training Phase*

Mean correct RTs for training trials were separately computed for homogeneous and heterogeneous search displays on the basis of group (see **Figure 5.2**). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 7.6% of the data). Condition means were entered into a mixed model repeated-measures ANOVA. Heterogeneous search displays produced longer RT ($M$ = 1,183 ms, $SEM$ = 38.9 ms) compared to homogeneous displays ($M$ = 1,024 ms, $SEM$ = 31.8 ms), $F(1,33) = 59.42$, $p < .001$, $\eta_p^2 = .64$. The group main effect was not significant, $F(2,33) = .39$, $p = .68$, $\eta_p^2 = .02$. Importantly however, the group x search display interaction was significant, $F(2,33) = 5.29$, $p = .010$, $\eta_p^2 = .24$. Follow-up *t*-tests

**Table 5.1** *Training phase mean accuracy for Exps. 10-12.*

| | | Hom. Search | | Het. Search | |
|---|---|---|---|---|---|
| | Group | *M* | SEM | *M* | SEM |
| Exp. 10 | Value-Feature | 0.927 | 0.020 | 0.925 | 0.023 |
| | No-Value | 0.971 | 0.007 | 0.956 | 0.011 |
| | Value-Singleton | 0.965 | 0.007 | 0.970 | 0.005 |
| Exp. 11 | Value-Feature | 0.980 | 0.005 | 0.978 | 0.004 |
| | No-Value | 0.957 | 0.010 | 0.970 | 0.006 |
| | Value-Singleton | 0.962 | 0.010 | 0.968 | 0.007 |
| Exp. 12 | Value-Feature | 0.944 | 0.025 | 0.948 | 0.031 |
| | No-Value | 0.954 | 0.017 | 0.960 | 0.009 |
| | Value-Singleton | 0.964 | 0.011 | 0.961 | 0.012 |

revealed larger RT for heterogeneous search displays than for homogeneous displays for all three groups (value-feature group: $M$ = 243 ms, $SEM$ = 45.7 ms, $t(11) = 5.32$, $p < .001$, $\eta_p^2 = .85$; no-value group: $M$ = 153 ms, $SEM$ = 31.3 ms, $t(11) = 4.89$, $p < .001$, $\eta_p^2 = .83$; value-singleton group: $M$ = 80 ms, $SEM$ = 27.3 ms, $t(11) = 2.92$, $p = .014$, $\eta_p^2 = .66$). These contrasts were all significant at the Bonferroni-corrected significance level of $p = .017$. To expose the nature of the above interaction, I reran the mixed model repeated-measures ANOVA as individual pairwise group contrasts. The results of these analyses revealed that the value-feature group produced a greater RT difference between the homogeneous and heterogeneous displays than the value-singleton group, $F(1,22) = 9.47$, $p = .006$, $\eta_p^2 = .30$, but the control group did not significantly deviate from either of the two other groups (both $p$s > .17). Mean accuracy data can be found in **Table 5.1**. There was no significant effect for an analogous analysis of mean accuracy (all $p$s > .10, all $\eta_p^2$s < .35).

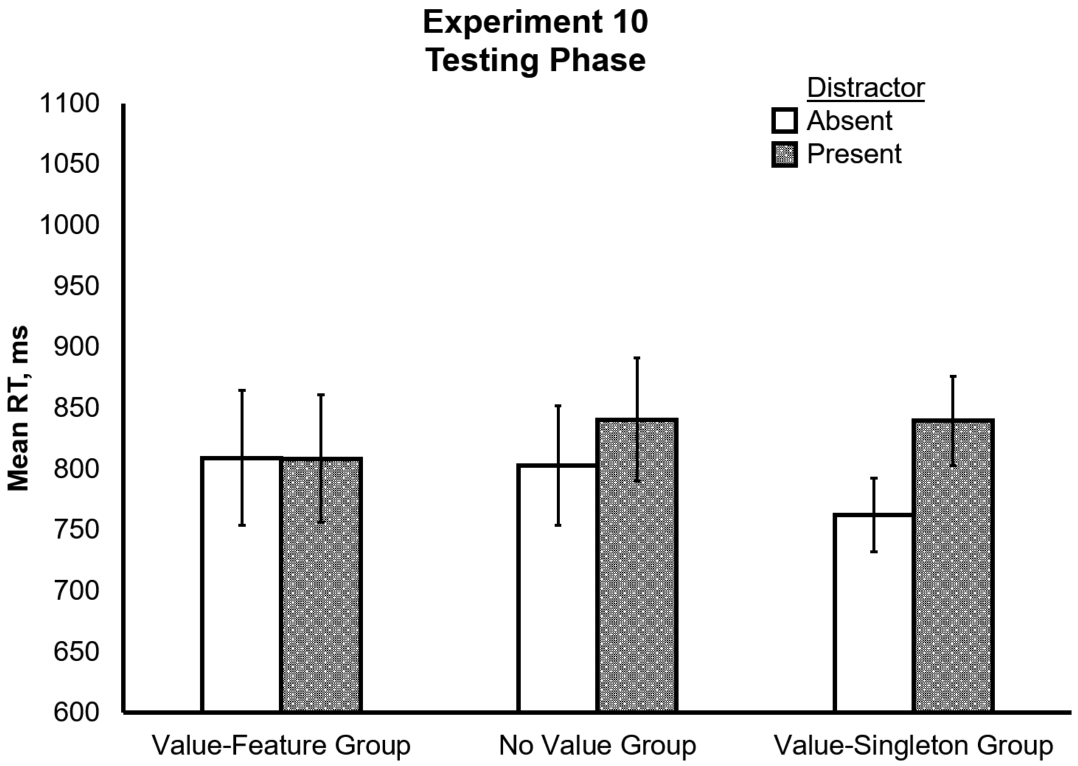

**Figure 5.3** *Experiment 10 testing phase RT.* Errors bars represent ±1 SEM

*Testing Phase*

Mean correct RTs for testing trials were separately computed for distractor present and absent trials (see **Figure 5.3**). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 7.4% of the data). Condition means were entered into a mixed model repeated-measures ANOVA. This analysis revealed a main effect of distractor status, $F(1,33) = 44.93$, $p < .001$, $\eta_p^2 = .58$. Distractor present displays ($M = 830$ ms, $SEM = 27.1$ ms) produced larger RT compared to distractor absent displays ($M = 791$ ms, $SEM = 26.6$ ms). The main effect of group was not significant, $F(2,33) = .052$, $p = .95$, $\eta_p^2 = .003$. Analogous to training, I observed a significant group x distraction interaction, $F(2,33) = 15.66$, $p < .001$, $\eta_p^2 = .49$. Follow-up analyses revealed a significant distraction effect for the no-value group and value-singleton group, but not the value-feature group (value-feature group: $M = -1$ ms, $SEM = 7.3$ ms, $t(11) =$

**Table 5.2** *Testing phase mean accuracy for Exps. 10-12.*

| | | Dist. Absent | | Dist. Present | |
|---|---|---|---|---|---|
| | Group | *M* | SEM | *M* | SEM |
| Exp. 10 | Value-Feature | 0.939 | 0.016 | 0.948 | 0.021 |
| | No-Value | 0.975 | 0.006 | 0.961 | 0.010 |
| | Value-Singleton | 0.962 | 0.008 | 0.961 | 0.006 |
| Exp. 11 | Value-Feature | 0.976 | 0.005 | 0.977 | 0.005 |
| | No-Value | 0.956 | 0.012 | 0.966 | 0.008 |
| | Value-Singleton | 0.972 | 0.006 | 0.963 | 0.007 |
| Exp. 12 | Value-Feature | 0.965 | 0.017 | 0.936 | 0.030 |
| | No-Value | 0.936 | 0.019 | 0.936 | 0.018 |
| | Value-Singleton | 0.971 | 0.006 | 0.968 | 0.007 |

.088, $p = .93$, $\eta_p^2 = .001$; no-value group: $M = 38$ ms, $SEM = 11.2$ ms, $t(11) = 3.36$, $p = .006$, $\eta_p^2 = .51$; value-singleton group: $M = 77$ ms, $SEM = 10.6$ ms, $t(11) = 7.31$, $p < .001$, $\eta_p^2 = .83$). Mean accuracy data can be found in **Table 5.2**. There was no significant effect for an analogous analysis of mean accuracy (all $p$s > .17, all $\eta_p^2$s < .35).

### 5.2.3 Discussion

In this experiment, rewards delivered during a training phase effectively biased attentional control in a subsequent testing phase. Amazingly, the effect of reward was two-fold. When participants were highly rewarded after completing a homogeneous search, they apparently persisted in singleton detection mode. At the same time, when participants were highly rewarded after completing feature search, they persisted in feature search mode. Critical group interactions were observed in training *and* testing phases, which implies that the groups were clearly processing the displays differently. Importantly, the only manipulated difference between the groups was the treatment of reward contingency to search display (ref. **Figure 5.1**). All participants were exposed to same number of homogeneous and heterogeneous displays. Therefore, there is no way that exposure alone could account for the pattern of results observed across groups. I propose instead that attentional control settings automatically adjust to reflect fluctuations in value-based environmental contingencies. Thus, in addition to feature-specific prioritization, rewards can throttle the attentional drive to adopt specific attentional sets. In doing so, rewards potentiate whichever search mode leads to the most reward. A similar priming effect can be induced by experience with a search mode in absence of rewards (Leber & Egeth, 2006a). However, the current work is novel in that it demonstrates search mode perseveration on the basis of reward value, not mere experience.

There is one study that shares some superficial similarities to the findings reported here, in which game rewards were employed in an operant paradigm to identify the putative default search mode (Kawahara, 2010). Kawahara (2010) trained participants in an option search task to identify the default search mode (as proposed by Einhäuser, Rutishauser, & Koch, 2008; Pashler & Harris, 2001). In the option phase, participants searched for a green circle amongst non-target green diamonds. Importantly, either singleton-detection or feature-search mode could be adopted. Kawahara was interested in determining the search mode that participants' would spontaneously choose. Game sound effects from Nintendo's Super Mario Brothers were delivered as rewards after correct performance. In a subsequent testing phase, participants searched for a green circle and on 50% of the trials a red diamond appeared as a distractor. On average participants were slower to respond when the diamond was present than absent, suggesting that participants were more likely to adopt singleton-detection mode. Kawahara concluded that participants' default search mode is the singleton-search mode.

There are some critical differences between Kawahara's study and the present findings: First, in my study, participants were trained with a mixture of search displays and then tested in an option phase. Second, the rewards used in my study obeyed an underlying association with the displays in training. Unlike my study, Kawahara did not differentially reinforce attentional set behavior but rather rewarded solely on the basis of correct performance. And while Kawahara's data suggest the singleton search mode as the default search mode, the results of Experiment 10 clearly show that participants tend to default to a mode that is neither completely stimulus- nor goal-directed. Instead, it appears that by introducing specific search display contingencies, rewards can motivate participants to adopt a search strategy that is more rigid or looser than the default setting. Therefore, Experiment 10 is the first demonstration of how rewards can throttle attentional control when probabilistically associated with search demands.

## 5.3 EXPERIMENT 11: GENERALIZATION OF SHAPED SEARCH MODES

In Experiment 10, I demonstrated the strong effect that rewarding stimuli have on search behavior. However, there is one alternative explanation that has to be ruled before such a strong conclusion can be drawn. That is, Experiment 10 still allows for the possibility that rewards shaped a specific low-level feature rather than a higher-level search mode. Specifically, during the training phase of Experiment 10, the target was usually a circle – it was always a circle for heterogeneous search displays and sometimes a circle for homogeneous displays. Participants in the value-feature were highly rewarded after heterogeneous displays and thus were more often rewarded after a circle-shaped target. In contrast, participants in the value-singleton group were highly rewarded after homogeneous displays and thus rarely after the target was a circle. Therefore, it is possible that rewards served to boost the salience of the low-level feature (i.e., circle) rather than shaping higher-order search strategies. The lack of a capture effect in the value-feature group could be explained by assuming that attention is more strongly drawn to the previously rewarded circular target rather than the distractor thereby attenuating capture. So the question is, can rewards operate to set the attentional system more generally, or do rewards rather require a clear link established to specific features. To distinguish between these two alternative explanations and to strengthen the argument that higher-level attentional sets can be influenced by reward, I conducted Experiment 11. This experiment resembled Experiment 10 but was aimed to rule out attentional capture based on low-level shape features. To this end, I switched the relevant target shape that participants were required to search for in the testing phase from a circle (as in Experiment 10) to a square. If rewards in the value-feature group are merely tuning attention to select the circle-shaped target, then there is no benefit for the value-feature group over the value singleton group to find a square-shaped target in the testing phase. However, if rewards shape the attentional system by priming higher-order search mode, then I expect to observe results that are consistent with Experiment 10 irrespective of target shape continuity.

### 5.3.1 Method

*Participants*

Thirty-six participants from the University of Iowa psychology research participant pool participated for partial course credit. Experiment 11 was identical to Experiment 10 except the target during the testing phase was a square.

### 5.3.2 Results

*Training Phase*

Mean correct RTs for training trials were separately computed for homogeneous and hetergeneous displays on the basis of group (see **Figure 5.4**). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 5.8% of the data). Condition

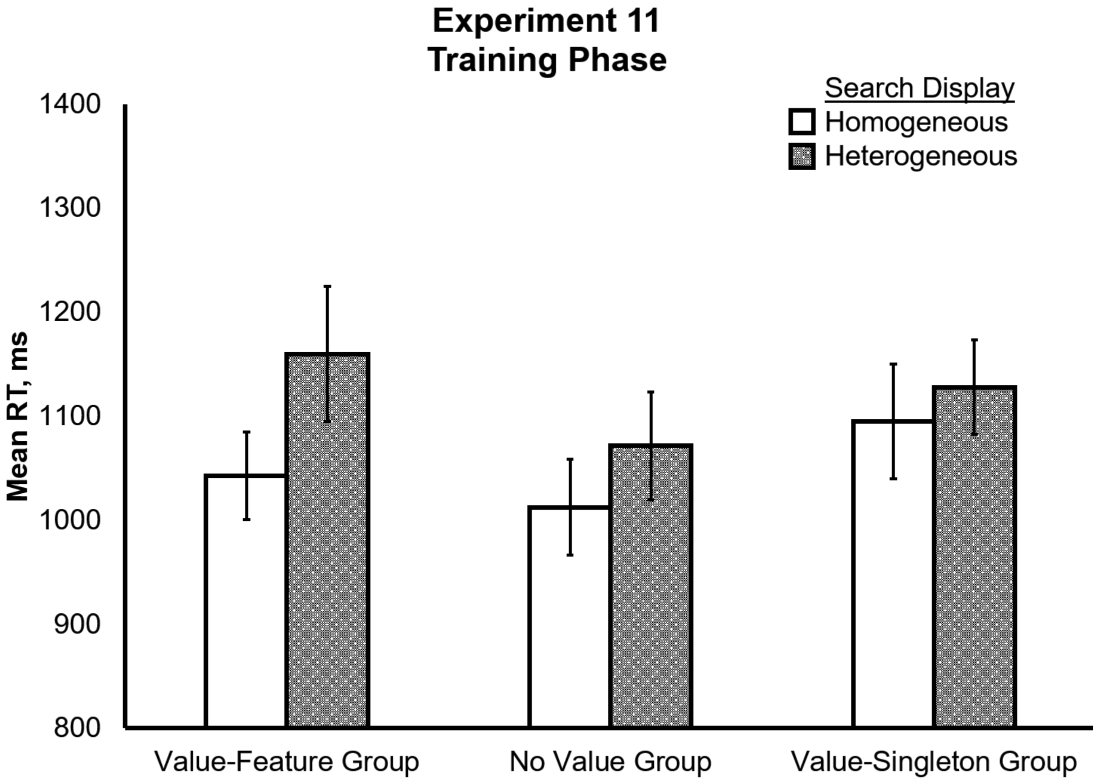

**Figure 5.4** *Experiment 11 training phase RT.* Errors bars represent ±1 SEM

means were entered into a mixed model repeated-measures ANOVA. The main effect of display type was significant, $F(1,11) = 9.92$, $p = .009$, $\eta_p^2 = .47$). Participants searched homogeneous displays ($M = 1050$ ms, $SEM = 46$ ms) faster than heterogeneous search displays ($M = 1120$ ms, $SEM = 52$ ms). The main effect of group was not significant, $F(2,22) = .68$, $p = .52$, $\eta_p^2 = .14$. Likewise, the interaction between group x search display was not significant, $F(2,22) = 1.41$, $p = .27$, $\eta_p^2 = .16$. Further, there was no significant effect for an analogous analysis of mean accuracy (all $p$s > .06, all $\eta_p^2$s < .36).

*Testing Phase*

Mean correct RTs for testing trials were separately computed for distractor present and absent trials (see **Figure 5.5**). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 6.3% of the data). Condition means were entered into a mixed model repeated-measures ANOVA. This analysis revealed a main effect of distractor status $F(1,11) = 68.56$, $p < .001$, $\eta_p^2 = .86$. Distractor present displays ($M = 835$ ms, $SEM = 43$ ms) produced longer RT compared to distractor absent displays ($M = 793$ ms, $SEM = 43$ ms). The main effect of group was not significant, $F(2,22) = .25$, $p = .78$, $\eta_p^2 = .04$. Importantly, the interaction between group x distractor was significant, $F(2,22) = 4.22$, $p = .028$, $\eta_p^2 = .32$. Follow-up analyses revealed a significant distraction effect for two groups: value-feature group, $M = 19$ ms, $SEM = 10.5$ ms, $t(11) = 1.81$, $p = .10$, $\eta_p^2 = .47$; no-value group, $M = 37$ ms, $SEM = 15.5$ ms, $t(11) = 4.54$, $p < .001$, $\eta_p^2 = .81$; value-singleton group, $M = 70$ ms, $SEM = 8.7$ ms, $t(11) = 3.96$, $p < .002$, $\eta_p^2 = .76$.

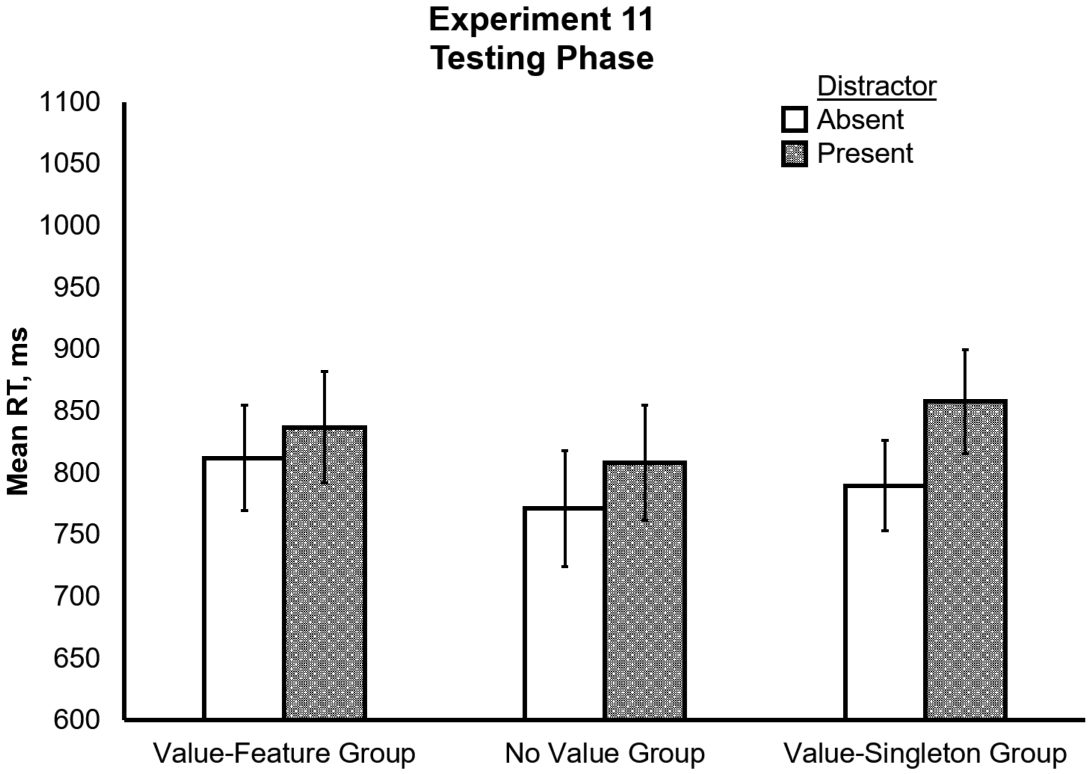

**Figure 5.5** *Experiment 11 testing phase RT.* Errors bars represent ±1 SEM

To directly address the interaction, I performed *t*-tests on the capture effect between pairs of groups. The extreme difference of attentional capture between the value-feature group and the value singleton group was significant, $t(11) = 3.03$, $p < .011$. The remaining contrasts were not significant (all *p*s > .09, all $\eta_p^2$s < .49). Further, there was no significant effect for an analogous analysis of mean accuracy (all *p*s > .24, all $\eta_p^2$s < .28).

### 5.3.3 Discussion

In Experiment 11, I controlled for feature-specific rewards effect by breaking the continuity of the target's shape between the training and testing phases. If feature-specific effects account for the value-feature advantage in Experiment 10, then this advantage should have vanished in Experiment 11. In contrast, the results of Experiment 11 clearly resemble the former results and thus support the idea that higher-level search modes can be shaped by reward. More specifically and in line with Experiment 10, I observed significantly higher attentional capture in the value-singleton group as compared to the value-feature group. In contrast to Experiment 10, there was a reliable amount of VDAC present for the value-feature group, which might suggest that additional feature-specific reward effects were at play in Experiment 10. However, the fact that VDAC was vastly reduced for the value-feature group as compared to the value-singleton group strengthens the argument that attention can be globally configured via implicit conditioning. Therefore, rewards can be deliberately structured to shape attentional behavior. In turn, this shaping effect produces lingering attentional set biases.

## 5.4 EXPERIMENT 12: SHAPED SEARCH MODES UNDER DYNAMIC DISTRACTION

In Experiments 10 and 11, I demonstrated how rewards can be used to implicitly tune global search settings. This finding is robust and was observed in training (Exp. 10) and testing

(Exps. 10 & 11) alike. In Experiment 12, I sought to provide further evidence for the independence of VDAC from low-level stimulus features like color.

In the VDAC, task there are two possible forces that work against each other: the attraction to the target stimulus and the attraction to the location of the distractor stimulus. VDAC can be reduced by either enhancing the selection of the target or by enhancing the suppression of the distractor (Sawaki & Luck, 2010). Similar to the concept of target templates, discussed in **Chapter 1.1**, distractor templates take time and experience to develop (Vatterott, 2015; Vatterott & Vecera, 2012). However, based on their similar nature, it is possible that participants who are in feature search mode would equally likely adopt target templates and distractor templates. As an even stronger test of whether abstract attentional sets can be directly rewarded, I sought to challenge the attentional system by hindering its ability to suppress the color distractor. To this end, I alternated the target and distractor colors on a block-wise basis, described as follows.

In section **5.2.1 General Methods**, I described the base color and distractor color. The base and distractor colors remained constant for a given participant in the previous experiments. In Experiment 12 however, I reduced the influence of distractor templates by changing the base and distractor color from block to block. This manipulation should hinder the successful suppression of distractor colors, because distractor colors change between blocks and can even be a former base color and could possibly be rewarded. I hypothesized that if distractor-specific suppression was responsible for the differential capture between value-feature and value-singleton group, then when I introduce dynamically changing colors, I should observe no difference in capture between the groups. Alternatively, if distractor suppression is not responsible for the observed differential capture, then I should still observe a difference in capture between groups.

### 5.4.1 Method

*Participants*

Thirty-six participants from the University of Iowa psychology research participant pool participated for partial course credit.

*Stimuli and Design*

Experiment 12 was identical to Experiment 11 except for the fact that the colors changed twice during the experiment: Once after the first train-test (AB) pair and once again after the second AB pair. The colors (red, yellow, and green) alternated in a specific pattern such that each color was the base color for exactly one AB pair and the distractor color for another AB pair. At the beginning of the experiment, a base color and a distractor color were randomly chosen for each participant. For instance, the first AB pair of the training phase started with the base color of yellow and the distractor color of blue. Crucially, when switching to the second AB pair, the initial distractor color blue became the new base color and the distractor became green. For the third and last AB pair, the base color was red and the distractor color was green. Thus color-selection for the current target color would serve to counteract any built up distractor-specific suppression. Furthermore, under these provisions, the participant would be unable to benefit from carry-over suppression from sequence to sequence. The color relationships were counterbalanced across participants.

### 5.4.2 Results

*Training Phase*

Mean correct RTs for training trials were separately computed for singleton and feature search displays on the basis of group (see **Figure 5.6**). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 7.2% of the data). Condition means

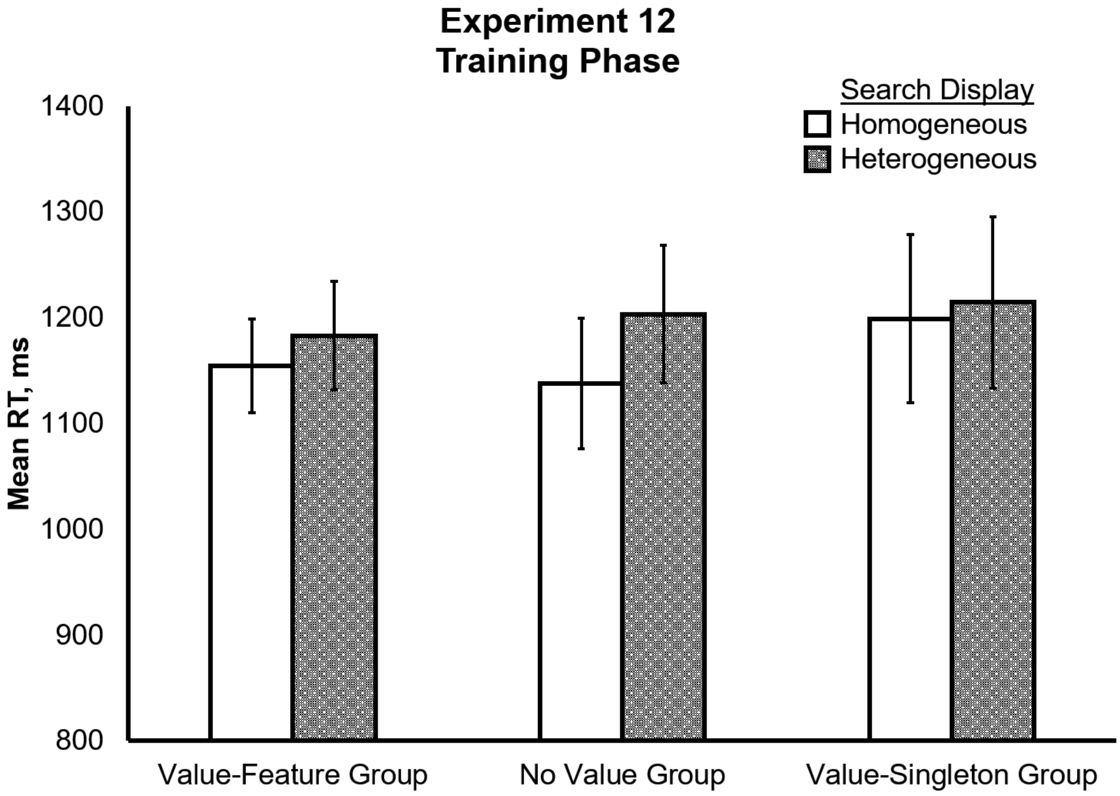

**Figure 5.6** *Experiment 12 training phase RT.* Errors bars represent ±1 SEM

were entered into a mixed model repeated-measures ANOVA. The main of effect of display type was not significant, $F(1,11) = 2.51$, $p = .14$, $\eta_p^2 = .19$). Additionally, neither the main effect of group, $F(2,22) = .18$, $p = .84$, $\eta_p^2 = .03$, nor the interaction between group and search display, $F(2,22) = .63$, $p = .54$, $\eta_p^2 = .01$, reached significance. Further, there was no significant effect for an analogous analysis of mean accuracy (all $p$s > .82, all $\eta_p^2$s < .13).

*Testing Phase*

Mean correct RTs for testing trials were separately computed for distractor present and absent trials (**Figure 5.7**). Incorrect trials and response latencies ±2.5 SDs of the mean were removed from analysis (this eliminated 7.9% of the data). Condition means were entered into a mixed model repeated-measures ANOVA. This analysis revealed a main effect of distractor status,

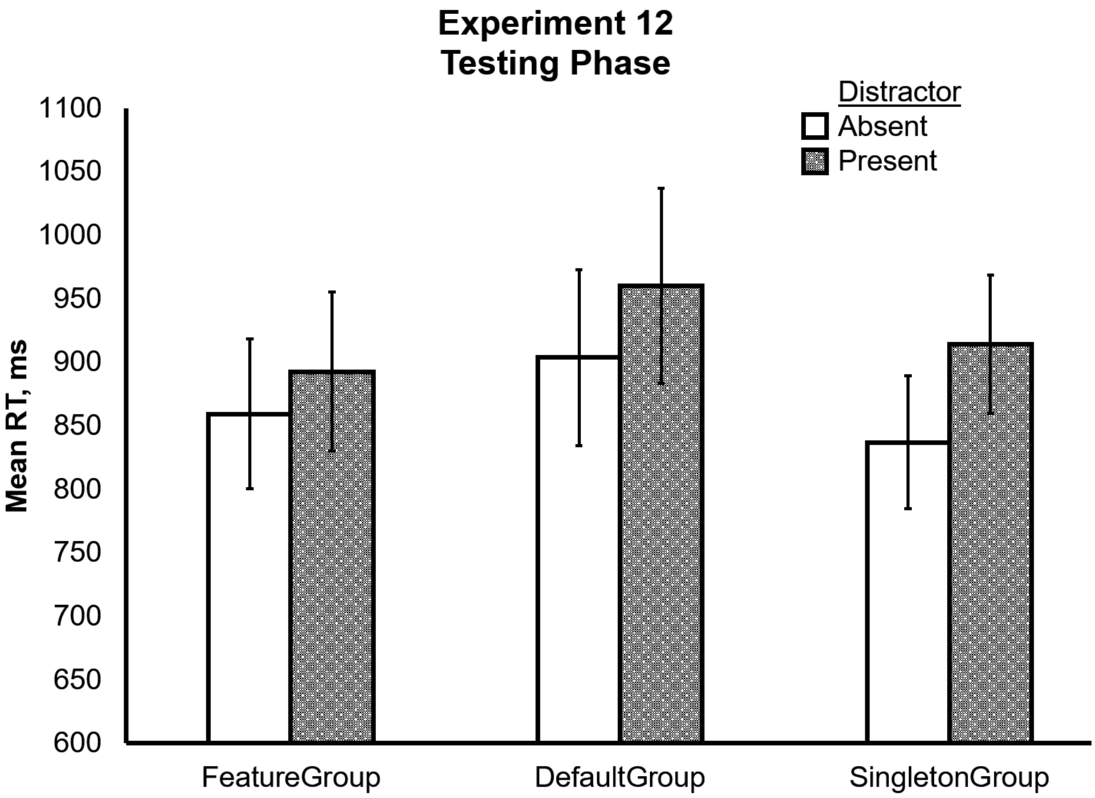

**Figure 5.7** *Experiment 12 testing phase RT.* Errors bars represent ±1 SEM

*F*(1,11) = 39.41, $p < .001$, $\eta_p^2 = .78$. Distractor present displays (*M* = 920 ms, *SEM* = 65 ms) produced larger RT compared to distractor absent displays (*M* = 865 ms, *SEM* = 60 ms). The main effect of group was not significant, *F*(2,22) = .60, $p = .56$, $\eta_p^2 = .06$. As in Experiment 11, I observed a significant group x distractor interaction, *F*(2,22) = 4.41, $p = .025$, $\eta_p^2 = .38$. Follow-up analyses revealed a significant distraction effect for each group: value-feature group, *M* = 32 ms, *SEM* = 14.0 ms, *t*(11) = 2.27, $p = .045$, $\eta_p^2 = .32$; no-value group, *M* = 56 ms, *SEM* = 12.7 ms, *t*(11) = 4.46, $p = .001$, $\eta_p^2 = .64$; value-singleton group, *M* = 77 ms, *SEM* = 10.4 ms, *t*(11) = 7.41, $p < .001$, $\eta_p^2 = .83$. The distraction effect for the value-feature group was not significant at the Bonferroni-corrected significance level of $p = .017$. Therefore, the capture effect was greater for the value-singleton group than for the value- feature group. Further, there was no significant effect for an analogous analysis of mean accuracy (all *p*s > .16, all $\eta_p^2$s < .21).

### 5.4.3 Discussion

The results of Experiment 12 add to the notion, according to which reward can shape higher-order human behavior rather than being restricted to influence mere low-level stimulus features. I demonstrated that rewarding feature search mode results in less VDAC by a singleton color distractor than rewarding singleton detection mode. This is true, even when the color of the distractor changes from block to block and thus contradicts a possible low-level and color-based distractor suppression mechanism. Together with Experiment 11, these results demonstrate higher-order, feature-independent effects of reward on the attentional set.

## 5.5 CHAPTER SUMMARY

Value-driven attentional capture effects are highly based on Pavlovian conditioning – that is rewards act to boost the priority of specific features. In addition, I demonstrated in **Chapter 5**, that rewards can likewise tune high-level attentional set behavior. In Experiments 11 and 12, I addressed potential alternative explanations such as feature-specific tuning to the target (Exp. 11) and distractor-specific suppression (Exp. 12). In all three experiments, I observed significantly more capture in the testing phase for the value-singleton group compared to the value-feature group. Rewards, therefore, throttle attentional control mechanisms in a manner that is dissociable from value-driven attentional capture.

Interestingly, rewards had a two-fold effect on the attentional set. Overall, the no-value group demonstrated moderate amounts of attentional capture. In comparison to the no value group, the value-feature group was resilient to capture and the value-singleton group was hypersensitive to distractors. This implies that rewards can encourage the adoption of a narrow set and at the same time it implies that rewards can ease attention into a diffuse set.

One possible way to conceptualize this finding is to consider the locus of attentional selection. The locus of selection can be set late, thereby allowing stimuli to reach a high-level of processing. This is the type of setting involved in homogeneous searches. In contrast, the locus of selection can be set early, thereby restricting attentional processing to task-relevant information. Serial searches require an early locus of selection. The locus of selection is flexible and can be set based of experimenter's instructions and the immediately surrounding visual space (Wolfe & Horowitz, 2004). Experience with a set leads to attentional set perseverance (Leber & Egeth, 2006a) Furthermore, the studies in **Chapter 4** demonstrate that rewards can throttle the locus of selection.

Lastly, the participants in Experiments 10-12 were never monetarily paid for their participation. As in **Chapters 2** and **3**, participants were not engaged to collect or earn the rewards used in the tasks. Therefore, global attentional processes are amenable to *implicitly* delivered rewards (i.e., images of U.S. dollar bill without remittance).

## 5.6 CHAPTER CONCLUSION

In conclusion, **Chapter 5** demonstrates an effect of reward on attention that is qualitatively dissociable from low-level feature associations. Importantly, these new data demonstrate how rewards may operate on the attentional system to produce behaviors that have strategic qualities (via a process similar to priming). Such an assertion supports a two-fold attentional effect. That is, rewards can be arbitrarily structured to encourage a participant to adopt one of two search modes – one that supports attentional engagement, feature-search mode, and another that encourages attentional disengagement, singleton-detection mode. This corresponds with recent work that suggests that rewards can be implemented to prime object categories (Hickey, Kaiser, & Peelen, 2015; Hickey & Peelen, 2015; but see Stilwell, 2015).

# 6 GENERAL DISCUSSION

In order to optimally behave in the world, input data must be parsed into relevant components. Visual selective attention guides this process by allowing only a subset of available input to receive further consideration (Desimone & Duncan, 1995). Consequently, attention is judicious, permitting the most relevant representations to carry on. Relevance, however, is situation-specific (Bacon & Egeth, 1994) and state-dependent. In the kitchen, the cues related to cooking do not necessarily correspond to those related to cleaning. Likewise, the environmental cues that are relevant to abate hunger do not necessarily correspond to those to abate thirst. Thus, what is attended is based on fluctuating environmental opportunities and changing goal states. Many factors contribute to relevance, but rewards have been shown to prominently influence selective attention (Anderson, 2013; Della Libera & Chelazzi, 2006; Raymond & O'Brien, 2009; Hickey et al., 2010; Krebs, Boehler, & Woldorff, 2010).

## 6.1 VDAC IS PREDOMINANTLY PAVLOVIAN

Recent demonstrations of rewarded attention have focused on feature-specific attentional priority set by stimulus-reward associations (Anderson, Laurent, & Yantis, 2011; Della Libera & Chelazzi, 2006; Della Libera & Chelazzi, 2009; Failing & Theeuwes, 2014). When rewards are paired with target specific (Anderson et al., 2011) or distractor specific (Le Pelley et al., 2015) perceptual features, then those features receive a boost in attentional priority. Drawing from decades old work in animal learning, we know that rewards can motivate behavior via at least two mechanisms – Pavlovian and operant conditioning. In **Chapter 3**, by substituting actual monetary rewards with mere images of bills as secondary reinforcers, I provided converging evidence that feature-specific value-driven attentional capture is primarily Pavlovian (Anderson, 2013; Le Pelley

& Pearson, 2015). Apparently, stimulus reward associations develop automatically without needing to be explicitly motivated-to-earn those rewards.

## 6.2 THE HOMUNCULUS VIOLATES EXPECTED UTILITY

Given the automaticity of feature-specific reward effects, in **Chapter 4** I sought to elucidate the economic behavior of the human visual system. Two competing hypotheses for the economic behavior of the attention homunculus were introduced – the attentional homunculus as a bean counter versus a fuzzy mathematician. I falsified the bean counter hypothesis by showing that the attentional system prefers high magnitude rewards over low magnitude rewards despite equal expected utility (ref. Exp. 5). Together with Experiments 6-9, I demonstrated that the value coding system within attention violates axioms assumed by expected utility theory (von Neumann & Morgenstern, 2007). I propose that stimuli in the environment are commoditized and weighted according to their reward-predictive value. In this way, reward signals in the brain can be recast as a currency that may be used to “grease the wheels” of attention. The neurotransmitter dopamine is a chemical messenger that could non-exclusively act as a currency in the brain (Ballard, 2015, p. 325).

## 6.3 SALIENCE IS A CURRENCY

The concept of a common currency can be applied to objects in the visual field too (Gottlieb, 2012). In this view, rewarded stimuli can convey an *attend-to-me* signal (Sawaki & Luck, 2010) that represents its current salience value. Therefore, each stimulus has an associated value based on its constituent features and furthermore, the visual system can perform computations on these values in order to optimally direct attention. It is well documented that different stimuli have different internally represented values (e.g., Deaner, Khera, & Platt, 2005).

In one study, male monkeys were forced to make a volitional eye-movement to one of two lateralized cues (C1 and C2). If they fixated C1, then they earned a juice reward (Deaner et al., 2005). However, if they fixated C2, then they were given a smaller juice reward but they were allowed to view monkey pornography – a strong reward for mating animals. Two forms of arousing images were tested – one image of a conspecific female monkey's perineum and one image of a lower-ranked cohort. After conducting a titration procedure, Deaner and colleagues were able to precisely determine the relative value of the images in units of juice. Images of conspecific perinea generated more looks overall and importantly, the researchers discovered that monkeys were willing to be underpaid in juice for the opportunity to view perinea. The fact that monkeys apparently pay-per-view to see arousing images suggests the presence of an internal value system where units of primary rewards (juice) are readily exchangeable with units of secondary rewards (looks). This finding is in line with my observations reported in **Chapter 4**; the human attentional homunculus behaves irrationally when faced with varying economic tradeoffs.

## 6.4 EXTENSION TO NOVEL VALUE SYSTEMS

The interpretation set forth herein stresses the role of mere exposure to rewards. One interesting extension of our findings applies to electronic cash (e-cash) systems. Societies around the world are becoming increasingly cashless. For example, the government of Denmark aims to phase out physical cash for in-store payments by 2016 (Fortune, 2015). Sweden is on verge of abandoning physical money altogether and has reduced the supply of physical currency by as much as 50% from 2008-2015 (KTH, 2015). Many consumers are already familiar with electronic banking. With the advent of blockchain technologies, such as bitcoin (Nakamoto, 2008), it will soon be possible to conduct any financial transaction from a mobile device. Despite these advantages over traditional cash, consumers have been sluggish to adopt e-cash. One cause of this reluctance may be due to our strong attachment with physical money, based partly on money's status as a secondary reinforcer. We handle money nearly every day and have learned its value by conducting countless cash transactions. We are familiar with money and there is comfort in its tangibility; however, there is every reason to expect that e-cash, despite its virtual nature, could also acquire such an elevated status. The present work demonstrated that mere images of money and even images of Monopoly money can be rewarding. This suggests that consumers could come to value e-cash as highly as physical cash provided they learn to associate reward with salient perceptual representations of e-cash (e.g., bitcoin denominated merchandise ₿ 0.1547, or other visual artwork in the form of a seal, emblem, logo, etc.). I posit that with frequent use and exposure, e-cash might someday become as relevant (psychologically speaking) as physical cash.

## 6.5 REWARDS SHAPE SEARCH STRATEGIES

Feature-specific associations strongly bias attention, but they cannot account for higher-order, strategic search behavior. In **Chapter 5**, I outlined a procedure to detect the effect of rewards on attentional set behavior. This task was unique in that rewards were specifically structured to encourage the use of feature-search mode in one group and singleton-detection mode in another group. I observed a two-fold effect of rewards. In comparison to a control group, rewards increased attentional capture when paired with homogeneous displays and also, rewards decreased attentional capture when paired with heterogeneous displays. Thus, bill images, when specifically implemented within a task, can throttle higher-order attentional set behavior.

In comparison to **Chapters 3** and **4**, the approach laid out in **Chapter 5** demonstrates an additional juncture for rewards to affect attention – higher-order behavior emerges from a pattern of stochastic association between search heterogeneity and reward value. Therefore, rewards can impinge on various representation layers within visual attention. On the one hand, feature-specific priming results from low-level reward associations and other the other hand, strategy-specific priming results from high-level reward associations. This dissociation is theoretically important because it can be used to help explain population-based differences in reward processing.

## 6.6 INTERPRETING POPULATION-BASED VDAC DIFFERENCES

The reinforcement learning framework makes it clear that there are at least two distinct levels for rewards to guide attention. This view allows for stronger, more comprehensive claims about population-based differences in reward processing. For instance, the VDAC task has been used to identify abnormal and underdeveloped reward processing in special populations. Anderson and colleagues have explored differential value processing in several special populations and found increased VDAC in persons with drug dependencies (Anderson et al., 2013) and HIV (Anderson et al., 2015) and decreased VDAC in persons with depression (Anderson et al., 2014). Additionally, my colleagues and I have demonstrated that VDAC is heightened in the adolescent population (see **Figure 6.1**; Roper et al., 2014). Generally, these findings have been used to argue for the presence of globally heightened/diminished reward sensitivity in these populations. However, it is not necessarily true that rewards act uniformly over the span of attentional processes in normal or abnormal populations.

The differences in value-driven attentional capture between special populations have been partially explained by appealing to individual variability in impulsivity and risk-seeking behavior. Unfortunately, the reinforcement learning framework has not been made explicit in the rewarded attention literature. Therefore population-based rewarded attention effects are difficult to clearly interpret. It is important to know how rewards are working to influence a behavior before we can make claims as to the reason why we observe population-based differences. Therefore, future use of rewarded attention tasks should adopt a complementary approach by studying the effect of rewards on low-level representations and the effect of rewards on high-level representations within these special populations.

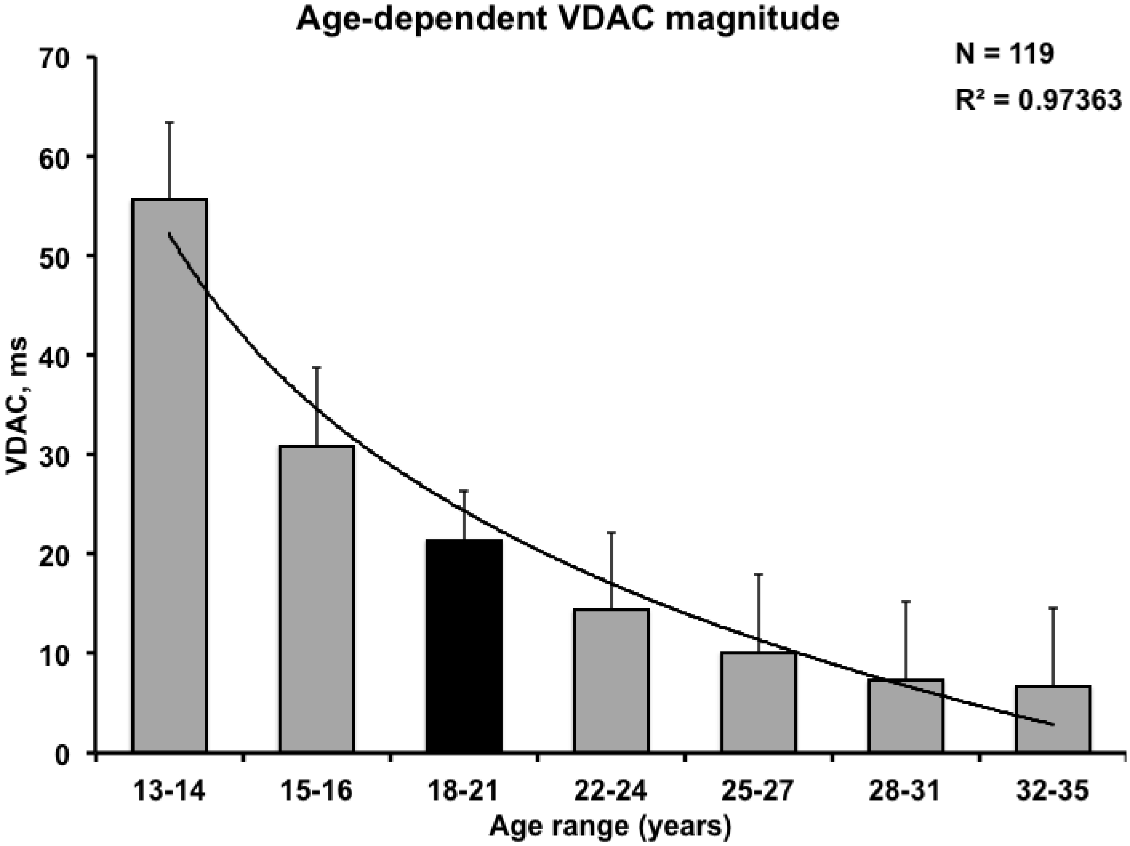

**Figure 6.1** *VDAC as a function of age.* The data depicted here represent value-driven attentional capture scores (RT in the presence of high-value distractors minus the RT in the presence of low-value distractors. The bars rendered in gray represent VDAC testing phase data from Roper, Vecera, and Vaidya (2014) and the bar rendered in black represents combined data from Experiments 1a and 1b in **Chapter 3**. Error bars represent +1 SEM

## 6.7 GENERAL REWARD-PRIMING FRAMEWORK

As described in the sections above, the differences in value-driven attentional capture between special populations have been explained, in part, by appealing to individual variability in risk tolerance. Adolescents, for example, might be generally more reward sensitive than their adult counterparts. However, such broad claims should be made with caution because rewards are not likely to behave uniformly across the various levels of visual representations. In fact, a major contribution of the work presented in this document is that attention can be feature-primed and/or strategy-primed through statistically associated reward feedback. Below, I propose a general framework by which to discuss the manifold roles of reward on attention. This framework deserves some explanation as it makes novel predictions about putative population-based rewarded attention interactions.

When rewards are probabilistically associated with specific visual representations, those representations are more likely to receive processing priority in future encounters. This is true of low-level representations (c.f., value-driven attentional capture, Anderson et al., 2011) and this is true of higher-order representations (i.e., shaped search modes, see **Chapter 5**, Roper & Vecera, 2015). Thus, rewards can prime low- as well as high-level representations via a positive feedback loop. This feedback loop acts on representation maps situated within representation space. **Figure 6.2** illustrates this model by depicting the visual processing stream embedded in a hierarchical representation space (for a general overview of this artitecture, see Rodríguez-Sánchez, Fallah, & Leonardis, 2015). In this representation space, low-level sensory and perceptual representations (e.g., edges, color, contrast, etc.) are situated nearest the input. Processing progresses to higher levels before reaching the output. This characterization places the highest-order representations nearest the global output end. Layers within this representation space monitor the information stream and perform computations on that information within the respective map.

In **Figure 6.2**, rewards are shown to act on just two of the many possible representation layers – a feature layer that codes for individual features such as shape, color, or contrast, etc. and a high-level layer that codes for high-order representations such as environmental context, complex patterns, and $n^{th}$-order spatial relationships. In this model, rewards can prime

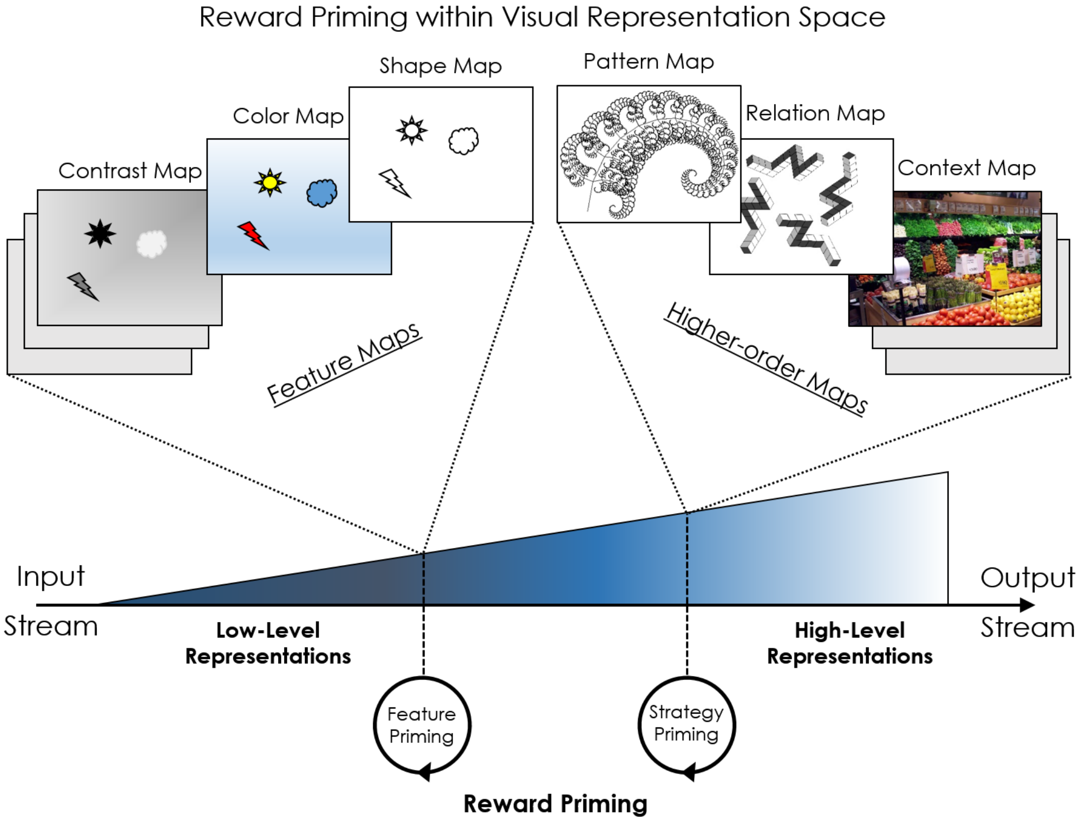

**Figure 6.2** *Manifold effects of reward feedback on the visual processing stream.* The figure depicts a hierarchical representation space (blue triangle) embedded within the visual processing stream (black arrow). The system has an input and an output with various processing layers in between. Individual maps are located throughout the representation space and become progressively more complex as they follow along the processing stream. Low-level maps perform computations on early visual information and are thus situated near the input. High-level maps code for complex relationships and are thus situated near the broader, more distributed end of representation space. It is likely that rewards can have an effect at several layers in this representation space; for simplicity, just two locations are depicted here. The left loop represents reward feedback that is stochastically associated with low-level feature maps. Rewards implemented at lower levels of representation space induce feature-specific priming (c.f., value-driven attentional capture, Anderson et al., 2011). The rightmost loop depicts reward feedback implemented in conjunction with higher order representations. When the rightmost loop is activated, attentional behavior conforms to strategy-like priming (c.f., Shaped Search Modes, **Chapter 5**)

representations at either or both levels. Rewards will prime a layer to the extent that a layer's constituent representations predict reward. Rewards paired with a specific color produce feature priming for that color and likewise rewards paired with specific search displays produce strategy-priming that resembles exposure-dependent search mode persistence (c.f., Leber & Egeth, 2006a). In the model, the reward loops activate representation maps. Those maps in turn prime their respective representations in a manner that suggests/resembles the attentional set. Reward priming, as characterized in this model, depends only on the sheer probabilistic contingency between the activation of a representation and the activation of a reward feedback loop.

This model brings about some interesting predictions when it comes to reward processing in special populations. For instance, adolescents show magnified attentional capture to low-level conditioned stimuli (Roper et al., 2014). This could be driven by heightened sensitivity to rewards or it could be due to underdeveloped executive control. The value-driven attentional capture task on its own cannot disambiguate these two possibilities and it is possible that both heightened reward sensitivity and underdeveloped control are responsible. However, given that feature-priming reward effects represent reward sensitivity at low representation levels and that strategy-priming reward effects represent reward sensitivity for high-level representations, then it might be the case that adolescents would show insensitivity to strategy-priming. Reward insensitivity at high-levels would manifest as executive dysfunction and strategy perseverance. Thus by considering how rewards operate to prime representations at various levels, we can form a clearer picture of the processes themselves. If adolescents are hypersensitive to rewards paired with low-level representations and hyposensitive to rewards paired with high-level representations, then perhaps it is because they lack the fully developed prefrontal structure to extract high-level patterns that are necessary to develop attentional strategies. Furthermore this leads to the direct prediction that adolescents and perhaps other populations would show heightened VDAC and at the same time a diminished ability to shape search modes suggesting a manifold role of reward on attention.

## 6.8 LIMITATION

By their very nature, rewards are arousing. Therefore, it is difficult to dissociate the effects of reward on attention from the effects of arousal on attention. It is important to realize that it may be impossible to completely dissociate the two, however. Although I never probed participants on their arousal, our choice to use relatively mundane images as rewards (i.e., money is encountered on regular basis) was intentional. Other rewarding visual stimuli (e.g., food, pornography, etc.) are arguably more arousing than images of bills. Thus, the choice of bills served to reduce potential arousal effects, however, it is still possible that the observed attentional effects are driven by reward but mediated by arousal.

## 6.9 CONCLUSION

In this document I draw from well-studied mechanisms of reinforcement learning (Pavlovian and operant conditioning) to establish a framework for rewarded attention tasks and motivated attentional behavior. When rewards are merely statistically paired with specific-features, those features are later prioritized. The results of **Chapter 3** and **4** support this conclusion. Likewise, when rewards are paired with search modes, those modes are later prioritized (see **Chapter 5**). Therefore, rewards and reward cues are powerful signals that have the potential to dominate attention at various levels of processing. Ultimately, reward signals shape overt behavior and exert a demanding influence over awareness.

# APPENDIX A: TASK KNOWLEDGE QUESTIONNAIRE

Questions were administered one-at-a-time and sequentially. Parts 1 and 2 refer to the training and testing phases respectively. Some representative answers are provided.

1. Did you believe you would be monetarily paid for your participation in today's experiment?

100% answered, "No."

2. What specific strategies did you use to perform the task?

"I looked for red and green and focused on that shape."

3. Did you notice any patterns in **part 1** of the experiment?

"No," and "Not sure but the flashes of the $20 and $5 may have repeated some sort of pattern."

4. Did you notice any patterns about the *colors* used in **part 1** of the experiment?

"I only paid attention to the red and green colors, the other ones did not stick out to me."

5. Did you notice any patterns about the *colors* used in **part 2** of the experiment?

"No, not really."

6. Did you notice any patterns concerning the *color* of the target-containing circle and the *money* in **part 1** of the experiment? If yes, please list any regularity you noticed.

"No, I wasn't sure what the money had to do with it."

7. In **part 1** of the experiment, the $20 bill appeared most often when the target was in a circle of a specific color. Which color was more likely to predict the $20 bill? If you don't know, please make your best guess. (Circle one) **GREEN** **RED**

50% responded correctly

8. In **part 2** of the experiment, sometimes a red or green circle appeared. Did you notice when a red or green circle appeared? (Circle one) **YES** **NO**

30% answered, "No."

9. Which color did you notice more? Make your best guess even if you answered "NO" to the previous question. (Circle one) **RED** **GREEN**

50% reported trying harder for the high-value color

## APPENDIX B: SUBJECTIVE MONETARY VALUE QUESTIONNAIRE

Questions were provided two at a time. One form (A, B) was administered per participant. Forms A and B were framed in terms of gains and forms C and D (not included here) were framed as losses. Data from the subjective value questionnaire are depicted in **Figure 4.1**.

<u>Form A</u>

1. You receive a message indicating you have won a large prize. You are asked to choose one of two prize options. (Circle one)
**Sure gain of $100**
**10% chance to gain $1,000**

2. You receive a message indicating you have won a small prize. You are asked to choose one of two prize options. (Circle one)
**10% chance to gain $40**
**Sure gain of $4**

3. You receive a message indicating you have won a medium prize. You are asked to choose one of two prize options. (Circle one)
**Sure gain of $10**
**10% chance to gain $100**

4. You receive a message indicating you have won a medium prize. You are asked to choose one of two prize options. (Circle one)
**10% chance to gain $200**
**Sure gain of $20**

<u>Form B</u>

1. You receive a message indicating you have won a medium prize. You are asked to choose one of two prize options. (Circle one)
**Sure gain of $8**
**10% chance to gain $80**

2. You receive a message indicating you have won a large prize. You are asked to choose one of two prize options. (Circle one)
**10% chance to gain $10,000**
**Sure gain of $1,000**

3. You receive a message indicating you have won a medium prize. You are asked to choose one of two prize options. (Circle one)
**Sure gain of $15**
**10% chance to gain $150**

4. You receive a message indicating you have won a small prize. You are asked to choose one of two prize options. (Circle one)
**10% chance to gain $10**
**Sure gain of $1**

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