July 2019

Mapping Reward Values to Cues, Locations, and Objects: The Influence of Reward Associations on Visual Attention

Constanza de Dios
University of South Florida, tanya.dedios@gmail.com

Mapping Reward Values to Cues, Locations, and Objects:

The Influence of Reward Associations on Visual Attention

by

Constanza de Dios

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
Department of Psychology
College of Arts and Sciences
University of South Florida

Major Professor: Geoffrey Potts, Ph.D.
David Drobes, Ph.D.
Chad Dubé, Ph.D.
Jennifer O'Brien, Ph.D.
Thomas Sanocki, Ph.D.

Date of Approval:
July 2, 2019

Keywords: Event-related potentials, attention, reward, P1, P2a, N2b

Dedication

My deepest gratitude to Erica Manuel and Thuy Phan for always being there. To BTS and ARMY for being a source of solace. To Mona El-Hout, Sophie Kuchynka, and Liz Kiebel for being my Tampa family. To Auntie Pinky and Uncle Dennis for being my surrogate parents.

I would also like to thank Hiroko Nakano, Mari-Anne Rosario, Maureen Little, Nushi Safinya, John Knight, all of the Psychology faculty at St. Mary's College of CA, and of course Lin Larson, who if not for her recruiting me to St. Mary's in 2008, my path towards my bachelor's and hence the doctorate degree might have been very different.

Thank you to all de Dioses and Cataylos for their endless support from either side of the Pacific Ocean. This is for Tito Gio and Dadski.

This is dedicated with love to Mama, Papa, Ate, Kuya Rom, Kuya, and Ate Heidi.

Acknowledgments

The biggest thanks to Heather Soder, Xiaoqian Yu, and Colleen O'Leary for being a significant part of my research life in the CECN lab. Thanks to all CECN lab research assistants who collected data for my projects through the years, with special mention to Taylor Haggerty, Rebecca Martinez, Alyssa Thompson, Vamshi Akula, Rebecca McDonald, Mark Zimmer, Joelle Castle, and Steven Ford for being the best examples of hard work, patience, and integrity. Carly Horner and Jaclyn Dell for showing me that goals can be reached no matter how long it takes. A special thanks to Jennifer O'Brien, Chad Dubé, and of course my advisor Geoffrey Potts, for providing invaluable guidance and reminding me to always follow the data.

Table of Contents

List of Tables

List of Figures

Abstract

Previous work has attempted to fit reward-driven attentional selection as being exogenous (stimulus-driven) or endogenous (goal-driven). However, recent work suggests that reward's effects on attention depend on the type of stimulus feature that the motivational information is imparted during learning (incentive salience). If true, then reward should not be limited to solely impacting early perceptual or late categorization processes attention. The current study used event-related potentials (ERPs) to test the idea that reward's effects on attention depend on the process that the reward information is embedded – early perceptual or late categorization. Results demonstrated reward-driven effects on perceptual representation when value information was conveyed by cues in a spatial cuing task, but did not find any value-driven effects when value was introduced later in processing in target-defined features in a target detection task. The current work suggests that reward can be rapidly acquired and sustained throughout a task, recruiting mechanisms of both exogenous and endogenous attention.

Introduction

Attention is the process through which the brain selects which information to prioritize over others for further processing. Selection is a process of distinguishing salient or relevant information from irrelevant information. Various methods can guide attention selection. In the lab, obeying instructions about stimulus features can guide one's attention (e.g., "Press a key when you see a number"), but in the real world, an individual's attention is more often guided by their own motivation (e.g., "What time is it? Let me look at my watch").

Attention is often conceptualized as a dichotomy: exogenous (bottom-up) and endogenous (top-down). Whereas exogenous or bottom-up (stimulus-driven) attention is "automatic", elicits attentional "capture", and is characterized by early perceptual representation (Näätänen, 1992), endogenous or top-down (goal-driven) attention is more effortful and requires later processing (Johnston & Dark, 1986; Theeuwes, 1994). While it is clear how stimulus features and goals drive attention, the ways in which motivational value drives attention are unclear.

The current investigation aims to elucidate how items of motivational or rewarding value capture attention through ERPs. While previous work has attempted to classify reward-driven attention as being exogenous or endogenous, recent work shows that reward-driven attention transcends this dichotomy, suggesting that learned value impacts processing depending on the type of stimulus features that the motivational information is embedded in (Rossi et al., 2017). Thus, if value information is attached prior to percept formation, effects are evident at or

prior to percept formation. If value information is attached later in processing, then effects must be evident after percept formation, at the level of stimulus categorization.

Exogenous Attention

Exogenous (also known as "bottom-up" or "stimulus-driven") attention often results from a phenomenon termed "automatic capture". Posner & Snyder (1975, as cited in Näätänen, 1992) stipulate that for a process to be automatic, it must occur with little effort or with little conscious awareness, is rapid, and is difficult to override. An automatic process, when irrelevant, will interfere with the task at hand. A classic example of such a process is the Stroop task, in which different color names are printed in color text and are presented one at a time to a subject. Results show quickened reaction times (RTs) to the congruent condition, but slowed RTs in the incongruent condition, demonstrating interference. This illustrates one way to measure automatic processes—the amount of interference they produce when they are irrelevant to the task.

Perceptual salience is a characteristic of exogenous attention, and can result in rapid capture. Items that are perceptually salient are said to "pop out". Motion and luminance (brightness) changes, for instance, are particularly noticeable when presented in brief pulses (less than a second). In cuing tasks, rapid motion and luminance changes are the best cues for reorienting attention, better than symbolic cues such as arrows (Posner, 2014). In a spatial cuing task, a central location for fixation is flanked by two boxes, one on either side, where a probe stimulus (*) is meant to appear on a given trial. The subject's task is press a key as soon as they notice the probe. Prior to the appearance of the probe, one of the boxes brightens; this is a luminance change. Sometimes the probe appears in the brightened box; this is a valid trial. Other times, the probe appears in a spatial location other than the brightening box; this is an invalid trial. Subjects' RTs are faster on valid trials than on invalid trials, indicating that the peripheral

cue rapidly drew their attention to the location, thus facilitating behavior targeted at whatever occurs subsequently in that location (Posner, Snyder, & Davidson, 1980).

The capability for rapid capture by a stimulus demonstrates early perceptual representation and its early access to limited processing resources ("early selection"). The capability of a stimulus to automatically capture attention can thus be observed as facilitated performance (quickened reaction times (RTs) or higher detection accuracy) in cuing tasks (Eriksen & St James, 1986; Posner et al., 1980). Other examples of capture occur in visual search in the form of enhanced detection of perceptual singletons when they are used as distractors (Theeuwes, 1994) or when they appear on displays of varying distractor set sizes (Treisman & Gelade, 1980).

Endogenous Attention

Endogenous (also known as "top-down") attention can be defined as selection based on current goals or schema. As opposed to exogenous (bottom-up) processing which is stimulus-driven, endogenous processing is goal-driven (Johnston & Dark, 1986; Theeuwes, 1994). One account of endogenous processing is sensory gain (Corbetta, Miezin, Dobmeyer, Shulman, & Petersen, 1990; 1991). In this model, signals coming from attended channels are enhanced. Corbetta and colleagues (1990; 1991) measured blood flow changes through PET (positron emission tomography) in subjects while they detected changes in color, speed, or shape of stimuli on a visual display. Subjects were instructed to pay attention to one attribute change at a time while all other attributes were kept constant—a selective attention condition (i.e. color changed while speed and shape were constant). On other blocks, subjects were instructed to attend to more than one attribute; this was a divided attention condition (i.e. both color and speed changed while shape remained constant). Results showed PET activation to the selective

attention conditions, in respective areas of cortex dedicated to processing the attribute. Attending to changes in color or shape activated extrastriate area V4; shape alone activated fusiform gyrus; color alone activated collateral sulcus; motion activated inferior parietal lobule (while this is not the motion-sensitive area MST, it is previously shown to be activated in smooth-pursuit tracking tasks in monkeys). These activations were over and above conditions where the same attributes changed but no instruction to attend was given (Corbetta et al., 1990). The activations were also decreased in the divided attention conditions (Corbetta et al., 1991)). This is evidence that attention to features based on goals or task relevance (in this case relevance to the task and coming from the instruction of the experimenter) enhances sensitivity in the specific sensory channel for that feature.

Unlike exogenous attention, endogenous attention requires control (Braver & Cohen, 2000). This is the ability to select a stimulus or event relevant to goals. Maintain goal representations is an ability of the prefrontal cortex (PFC), biasing incoming signals from other parts of cortex, in order to resolve mismatch and produce an output such as a motor response (Braver & Cohen, 2000). Top-down control is important for monitoring and resolving conflict produced by incompatible information from multiple input channels (Botvinick, Braver, Barch, Carter, & Cohen, 2001), and is evident when selection must be wielded in instances where multiple stimuli compete, as is the case in visual search (Theeuwes, 1994; Treisman & Gelade, 1980). Unlike exogenous attention, where attention exerts its impact early (prior to percept formation), endogenous attention requires control via the evaluation of relevance of stimuli. This necessarily occurs after perceptual representation, at the stage of stimulus categorization and evaluation, potentially occurring in the frontal cortex.

Neural Mechanisms of Exogenous and Endogenous Attention

Exogenous and endogenous attention are thought to activate overlapping but separable mechanisms. Their overlap lies in the frontoparietal network, which broadly includes an anterior network (including anterior cingulate cortex or ACC) and posterior sensory cortex (Katsuki & Constantinidis, 2014). What distinguishes exogenous from endogenous attention in terms of this network is what general region gets activated first, or more strongly: posterior for exogenous, anterior for endogenous (Buschman & Miller, 2007).

While exogenous attention recruits the posterior attention system (Buschman & Miller, 2007; Corbetta et al., 1991; Posner & Petersen, 1990), endogenous attention recruits the anterior system, which includes prefrontal cortex (PFC) and anterior cingulate cortex (ACC) (Botvinick et al., 2001; Braver & Cohen, 2000; Buschman & Miller, 2007; Corbetta et al., 1991; Desimone & Duncan, 1995; Miller & Cohen, 2001; Posner & Petersen, 1990). Posner & Petersen (1990) implicated this anterior system in target detection, noting that lesions to the frontal region in humans lead to the inability to detect instructed targets, and that more ACC activity was proportional to the number of targets that needed to be detected at any one time in experimental tasks. In the same study by Corbetta et al. (1991) mentioned previously, the divided attention condition, where participants had to exert control in figuring out which attributes were changing in a display, produced a different pattern of activation in the brain compared to the selective attention condition. Divided attention produced much weaker activations in modality-specific cortex, and instead produced greater activation in one region – the ACC. This suggests that the ACC has some role in effortful control.

The reasons the PFC and ACC are crucial in the anterior system are outlined by Cohen and colleagues, with work building on Desimone and Duncan (1995) who showed that

during selective attention and regardless of sensory modality, PFC is more active and is likely responsible for biasing sensory pathways in competition with each other. The PFC, with its role in working memory, maintains goal representations and is thus able to provide both a bias signal to sensory pathways that are behaviorally relevant (Braver & Cohen, 2000). According to Miller and Cohen (2001), PFC is a prime candidate for the source of this biasing signal because it has a large capacity for multimodal integration, is active despite distraction until a goal must be achieved, and exhibits plasticity. Its multimodality is exhibited by the following: its multiple sensory inputs from disparate parts of posterior cortex (occipital for visual, parietal for somatosensory, temporal for auditory) to dorsolateral PFC; its motor outputs from medial PFC to premotor and presupplementary motor areas in the frontal lobe; and its limbic connections to hypothalamus and amygdala. In delay-to-matching tasks, PFC neurons in monkeys are active during the delays between a cue and the behavior, even when irrelevant distractors are present during delays, showing that PFC maintains representations despite distraction. PFC neurons also enhance responses to cues that they were initially insensitive to but are behaviorally relevant, showing their plasticity.

Unlike the posterior attention system, the anterior system is not modality specific, and receives input from a wide variety of sources, providing it the capability to bias signal to different outputs.

Reward-Driven Attention

While plenty of evidence provides support for exogenous and endogenous attention, recent work has called into question how "clear-cut" this dichotomy is. For the majority in the field, the two components are not mutually exclusive. In fact, more recent accounts attempt to go beyond them, or at least make room for both. (One such account is the normalization model of

attention by Reynolds & Heeger [2009], a largely bottom-up account with room for top-down control). While some accounts attempt to move beyond the dichotomy through a complete revision of our conceptualization of attention, other work has generated evidence prompting for a slight adjustment to our dichotomous description of attention. Most of this work has been in reward and value learning, to which I turn next.

Evidence shows that a stimulus that had been selected multiple times previously can gain privileged processing in a subsequent task, suggesting a role for selection history in driving attention, independent of stimulus properties or task goals (for further discussion on selection history, see Awh et al., 2012; Failing & Theeuwes, 2017). More specifically, selection due to value associations has been shown to impact attention, with no easy support using only explanations of exogenous or endogenous processing.

On the one hand, reward-driven salience has been shown to exhibit effects often ascribed to exogenous attention, such as capture. Capture effects are dramatically illustrated in two-phase experiments in which participants learn to associate reward to otherwise perceptually neutral stimuli in an initial training phase, and then are shown the same stimuli in a separate test phase (Anderson, Laurent, & Yantis, 2011a; Chelazzi et al., 2014; Failing & Theeuwes, 2014; Raymond & O'Brien, 2009). In the first phase, correct behavior to certain stimuli or stimulus features (usually color) is rewarded and participants are encouraged to maximize earnings, so that reward is mapped to the stimuli and are relevant. In the second phase, no rewards are delivered, and the task is no longer to maximize earnings but to make some kind of perceptual decision, thus reward is irrelevant in the test phase. Anderson et al. (2011) trained participants to associate varying amounts of reward (points) with a color. Participants then performed a visual search task with an additional singleton, e.g. look for the green diamond in a multielement array

of eight stimuli, six of which are green circles, one is a green diamond, and one is a red circle (the green diamond is the target, the red circle is the 'additional singleton'; this is the same procedure used by Theeuwes, 1994.) Anderson et al. found that when the additional singleton was in a color previously associated with reward in the training phase, target reaction times (RTs) were significantly slowed compared to when the additional singleton color was not associated with reward. Failing and Theeuwes (2014) found similar results when they used a Posner cuing task as the test phase: faster RTs to the target when it appeared in the circle whose color signified reward in an earlier training task.

Raymond and O'Brien (2009) also found evidence for capture due to learned value, specifically reward. They trained participants to associate win, loss, or no values to computer-generated face stimuli in an initial learning task; participants then performed a subsequent attentional blink (AB) task in which two stimuli were serially presented with short or long lags in between. The second of the two stimuli were either the trained faces in the learning task, or novel faces. Participants were to report on the identity of both targets appearing in the stream. In AB, report for the second target fails when presented at short (~200ms) lags within the first target, with report recovering at longer (~800ms) lags. Thus, if value had no impact, then the faces associated with win or loss would elicit typical AB behavior; suffered report at short lags, successful report at long lags. But this was not the case. Faces that were associated with wins actually escaped the AB period, with probability for report being more successful than other types of stimuli. It should be noted that all the faces were perceptually similar, including the faces that were not part of the training task but were included at test, so the effect induced by the win-associated faces was not due to their perceptual salience. Instead, it was their value

associations—specifically with win or positive value—that produced the capture during the AB period.

While reward-associated stimuli induce capture akin to perceptually salient stimuli, they are still qualitatively different from perceptually salient features (color, brightness, motion, etc.) in that the reward imparted upon them is not inherent but must be learned, just as in endogenous attention. Such learning, or the imparting of value to a stimulus, occurs through incentive salience.

Incentive Salience and Reward Association

Incentive salience is a characteristic of stimuli or events that grab attention because they are "wanted" by the observer, due to their rewarding properties (Berridge & Robinson, 1998; Schultz, 2002). Berridge and Robinson distinguish incentive salience from the hedonic impact or "liking" of rewards, arguing that hedonia is an *effect* of receiving rewards, whereas incentive salience is something imparted on a stimulus that *causes* the seeking or "wanting" of it. In support of the "wanted" aspect of reward is the capture induced by rewarded stimuli, described previously. While incentive salience exhibits similar properties as perceptual salience, it is also unique in that it often entails learning. Such learning has been conceptualized in terms of reinforcement learning, such that an organism's behavior is reinforced to make such behavior more frequent. One model of reinforcement learning is the temporal difference (TD) algorithm (Schultz, 2002). Dopamine (DA) neurons, the majority of which are in the substantia nigra/ventral tegmental area complex, calculate a TD signal, with 80% of these neurons specific to reward. TD is a measure of the difference between the anticipated time/amount of reward and the time/amount of reward experienced.

DA neurons calculate TD signal in terms of prediction error. Unexpected reward or outcomes that are better-than-expected (increased spike rate) produces a positive prediction error. Outcomes that are as-expected (no change in spike rate) produce a zero prediction error. Unexpected non-rewards or worse-than-expected outcomes (decreased spike rate) produce a negative production error. When the prediction error is zero, there is no new information to be learned. In the above example, when the light, completely predictive of the natural reward, is paired with a sound, the sound induces no further increase in spike rate, thereby producing no prediction error. This is because the sound has no additional predictive information. Meanwhile, a nonzero prediction error indicates something new to be learned (Schultz, 2002). Learning to anticipate reward is a learning signal. Importantly, DA neurons respond to the conditioned stimulus in the same way they respond to natural rewards. It is in this way that conditioned stimuli acquire incentive value—by learning that they reliably predict reward (Berridge, 2007). Thus, incentive salience or the "wanted" attribute of reward, is brought about by reinforcement learning.

One then might argue that reward-driven attention is more like endogenous attention. However, selection by reward and selection by goals are still distinguishable from each other. Paradigms that incorporate instructed targets and irrelevant rewarded distractors allow a useful comparison of value-associated stimuli with stimuli that must be selected according to current *top-down* goals; if valued stimuli interfere with or produce a different effect than the instructed stimuli, we distinguish value as being different from top-down selection (Chelazzi et al., 2014; Munneke, Belopolsky, & Theeuwes, 2016).

Chelazzi et al. (2014) made use of a training-test paradigm in which participants learned to associate reward values with spatial locations and were tested in a subsequent search

task. Chelazzi et al. gave complementary probabilities of different amounts of reward in one of eight discrete locations surrounding the center of a display (e.g. one location gave high reward 80% of the time but low reward 20% of the time; another gave low reward 80% of the time and high reward 20% of the time). In subsequent test, participants were presented one or two targets at once; participants had to indicate which targets they saw. Chelazzi measured priority by only taking trials where two targets were presented but only one was reported, and measuring probability of report. They found that when two targets appeared at the same time in the visual search display during test, and participants correctly identified only one of them, they were better able to identify targets that appeared in locations associated with high-probability high-magnitude rewards, compared to targets occurring in locations related to low-probability low-magnitude rewards. Hence it is possible to imbue reward onto spatial locations.

Munneke et al. (2016) did not employ a separate training phase as did the previous studies described, but found similar results. They made use of the additional -singleton paradigm used by Theeuwes (1994), but introduced a fully-valid central arrow to be used as an endogenous cue pointing to the relevant target. The additional but irrelevant singleton was a color circle associated with points; these points were given as feedback after every trial. Different reward amounts were assigned to specific colors; these colors appeared randomly throughout the trials. Results showed that participants' RTs to the instructed target were significantly slowed on trials where a color associated with a high reward appeared. The same results held even when trial types were interleaved and not blocked (ruling out inter-trial priming or history), and even when the potential for reward was infrequent (discouraging reward-seeking behavior), suggesting that the attention elicited by reward can run counter to and even impede attention driven by one's goals.

To summarize, attention selection due to value association (via learning) can be distinguishable from exogenous capture because the same stimuli, when not associated with any value, do not produce the same capture effects. This is indicated by comparisons with reward-neutral stimuli, signifying that there is nothing special about the stimuli as far as physical properties are concerned. At the same time, reward-driven selection is not the same as endogenous control because value-associated stimuli can still produce capture in spite of current task (top-down) goals, thus they can be disentangled. This is evident in interference effects with instructed targets when value-associated items are also present in the same display.

Measuring Attention: Event-Related Potentials

Event-related potentials (ERPs) have excellent temporal resolution, allowing examination of specific stages of perceptual processing that attention has an impact. ERPs will be the main measure in the current study. The earliest ERP indices of attention are the P1 (90-110ms) and N1 (100-170ms) components (Hillyard & Anllo-Vento, 1998; Luck, Heinze, Mangun, & Hillyard, 1990). Emanating from occipitotemporal leads, both components are larger to stimuli in attended locations. The P1 and N1, however, are dissociable, and may signify distinct aspects of sensory facilitation of attended stimulus inputs. A stimulus appearing in a spatial hemifield that was cued by a stimulus on the prior trial elicits a larger P1 on the subsequent trial (Luck et al.). This suggests that the P1 indexes sensory enhancement prior to the onset of a stimulus in the attended location. The N1, meanwhile, becomes larger to stimulus onset in a previously unattended hemifield compared to if it appeared in a previously attended hemifield (Luck et al.). This indicates a somewhat different process for the N1, that of orienting to the appearance of a stimulus in a previously unattended location. The respective effects for the P1 and the N1 remained the same regardless of whether the eliciting stimulus was an instructed

target or a nontarget. Thus, the P1 and N1 are indices of exogenous (stimulus-driven) attention, with the former indexing enhancement prior to stimulus onset, and the other measuring orienting to novel spatial locations.

Perceptual representation that occurs a bit later, at the stage of object categorization, can be indexed by a selection negativity, the N2b (200-300ms). The N2b is part of a family of components of the N2, traditionally thought to index object discrimination (Woodman, 2010). Potts and Tucker (Potts & Tucker, 2001) measured the N2b in participants performing two types of target detection tasks, one for objects and one for spatial location. Four placeholder boxes remained on the screen, and one of four symbols appeared in one of the boxes. In object target detection, they pressed a key when one of the four symbols appeared in any of the boxes. In spatial target detection, they pressed a key when any of the four symbols appeared in one of the boxes. The N2b was measured separately over ventral posterior and over dorsal posterior leads. The idea was that the 'what' pathway (ventral) would be more active during the object detection task, while the 'where' pathway (dorsal) would be more active in the spatial detection task. This was supported: they found that the N2b was much larger over ventral posterior electrodes in response to targets in the object selection task compared to the spatial selection task (a ventral N2b), and larger over dorsal posterior electrodes to the spatial targets compared to object targets (a dorsal N2b).

Potts & Tucker (2001) measured another ERP occurring at the same time as the N2b. The P2a (200-300ms) over mediofrontal leads indexes frontal evaluation of relevance (Potts & Tucker, 2001), thus it is sensitive to top-down influences. Unlike the P3, it is larger to instructed targets than nontargets irrespective of stimulus frequency (Potts, Patel, & Azzam, 2004). ERPs to the onset of the symbols in Potts & Tucker (2001) showed an enhanced P2a to the targets

compared to the nontargets. This effect was the same whether the instructed target was a symbol in the object detection task, or a specified location in the spatial detection task. Thus, the P2a measures 'target-ness' or top-down evaluation of relevance. Unlike the N2b which changes topographical distribution corresponding to the pathway of the object feature being selected, the P2a stays put over frontal cortex regardless of the object being selected. Hence the P2a indicates later perceptual processes, being a sensitive measure of subjective relevance and top-down selection. For this reason, it can be used to measure later aspects of attentional selection, particularly endogenously driven (top-down) attention.

The Current Study

The current investigation aims to elucidate how reward drives attention. While previous work has attempted to classify reward-driven attention as exogenous or endogenous, recent work has shown that reward exerts effects that cannot easily fit within the dichotomy. The reason could be due to incentive salience, or the imparting of (reward) value on a stimulus (Berridge & Robinson, 1998). Evidence for this comes from value-learning paradigms that suggest value associations are maintained across time. For instance, stimuli or stimulus features previously associated with reward continue to facilitate detection when they are subsequent task targets, but no longer rewarded (Failing & Theeuwes, 2014), and interfere with target detection when they are distractors (Anderson, Laurent, & Yantis, 2011b; Munneke et al., 2016). This appears to be the case when the stimuli are cue colors (Failing & Theeuwes, 2014) or spatial locations (Chelazzi et al., 2014).

Recent evidence suggests that reward learning produces changes in behavior over time during training (Failing & Theeuwes, 2014), supporting the idea that incentive salience is responsible for attaching reward value to stimuli. In Failing & Theeuwes' design, participants saw two differently colored circles on the screen, each flanking a central fixation cross. One circle always contained one of two target letters, and the other always contained one of two distractor letters. The participants' task was to press one of two keys that corresponded to the target letter that appeared. In an initial training phase, these "trained circles" (ones that contained the target letter) could have one of two colors, one associated with reward or another associated with nonreward (loss). Two other colors were not associated with any reward but never

contained the target letter ("non-trained circles"). Each trial during the training phase ended with feedback indicating the reward they earned. During a subsequent test phase, participants performed the letter discrimination task but were informed that no reward would be delivered; the color of the circles and hence the reward information were irrelevant. Results from the training phase showed that not only were participants faster to press the key to the rewarded target circles, but were more so during the later blocks, indicating that the learning of the reward associations facilitated behavior over time during training. At test, when the trained circles were no longer predictive of any reward information, participants were still faster to the circles previously associated with reward compared to circles not associated with reward, but this effect did not change through the blocks, suggesting that the reward associations remained stable over time.

Reward-driven effects such as those described above are evident when value is associated with objects or stimulus features, indicating that effects are observable at least at the stage of object discrimination. Recent work, however, suggests that reward effects can occur at an earlier process, during spatial representation (Chelazzi et al., 2014; Failing & Theeuwes, 2014). Chelazzi et al. (2014) trained participants to associate rewards of different magnitudes in complementary probabilities across distinct spatial locations on the screen (i.e., two nonadjacent locations were designated to deliver a high reward 80% of the time and a low reward 20% of the time, whereas two other locations gave a high reward 20% of the time and a low reward 80% of the time; the remaining two locations gave high and low rewards at a rate of 50% each). In a subsequent search task, when they measured target detection accuracy on trials in which two probe targets were presented and needed to be identified, one in the location previously associated with 80%-high reward and the other in the location previously associated with 20%-

high reward, only one target was successfully identified. The likelihood of correct target identification was better in the 80%-high reward compared to the 20%-high reward location. Thus locations previously associated with higher expected value were differentially attended compared to those with low expected value, indicating that value can be attached to stimuli at a stage as early as spatial representation.

If incentive salience is the reason for such reward effects, then reward-driven selection should not be limited to impacting only exogenous (early) or only endogenous (late) selection processes. In the current study, I test the idea that the impact of reward depends on the process in which the value information is introduced: early attachment of reward produces exogenous effects (spatial representation), while later attachment elicits endogenous effects (stimulus categorization or evaluation). Previous evidence suggests that incentive salience can be attached late, to objects and object features, while more recent work indicates that earlier attachment is possible, as in the case of spatial locations. However, these studies did not control for the stage in processing or the type of object feature that the value information is introduced. The current study manipulates the process that incentive salience is introduced (spatial representation or object categorization) and controls the reward value being imparted.

Study 1 tests the idea that when value information is attached at the level of perceptual/spatial representation, effects should be limited to changes in spatial attention indices P1 and N1. Study 2 tests the idea that when value information is attached at the level of stimulus categorization, effects should occur on the perceptual ERP indices specific to the target feature imbued with reward (dorsal N2b if rewarded location, ventral N2b if rewarded object). Value-driven effects should also be observed in the P2a index of instructed relevance regardless of the type of stimulus feature being imparted with reward.

Specific Aims

The current study addressed three aims:

Aim 1. Perceptual representation and instructed relevance are distinct cognitive operations, thus their neural indices will possess distinct spatio-temporal distributions. Perceptual representation will engage the posterior attention system, eliciting changes in the P1, N1, and N2b ERPs, while instructed relevance will engage the anterior system, as indexed by the P2a, replicating previous work (Luck, Heinze, Mangun, & Hillyard, 1990; Potts & Tucker, 2001).

Aim 2. Acquiring reward value associations produces a change in behavior over time, hence stimuli acquire incentive (reward) salience through learning (Berridge & Robinson, 1998; Chelazzi et al., 2014; Failing & Theeuwes, 2014). Behavior and neural responses to stimuli that are not associated with motivational value will stay consistent across time, but will be modulated to value-associated stimuli.

Aim 3. Reward salience is not limited to impacting solely exogenous (early) or endogenous (late) selection processes; value exerts its effect depending on the stage in processing that the value information is imparted. Hence value-driven effects on perceptual measures will depend on the type of stimulus that the motivational information is embedded in. If value is attached to spatial or early perceptual representation, effects of value will be observed at the stage of percept formation: value attached to cued locations will elicit changes in the amplitudes of P1 and N1. Value attached after percept formation to spatial locations will elicit changes in the amplitudes of the P1, N1, and dorsal N2b ERP indices of spatial selection, but not the ventral N2b ERP index of object categorization. Value embedded in stimulus shape will

modulate the amplitude of ventral N2b but not of the P1, N1, or dorsal N2b. Finally, value conveyed at the level of target selection will enhance the P2a index of relevance evaluation, regardless of the reward-associated stimulus feature.

Study 1: Aims

Study 1 conveyed reward information through cues in a spatial cuing task. Below are predictions for each aim specific to Study 1.

Aim 1. Perceptual representation and instructed relevance are distinct cognitive operations, thus their neural indices will possess distinct spatio-temporal distributions. [1]

H1a: The P1 and N1 ERPs, indexing sensory enhancement prior to the appearance of a stimulus, will be larger to cued than uncued stimuli, regardless of target or reward identity (Main effect of Cue) (Study 1).

H1c: The P2a, indexing instructed relevance, will be larger to instructed targets than nontargets (main effect of Stimulus), regardless of cue or reward (Study 1).

Aim 2. Acquiring reward value associations produces a change in behavior over time, hence stimuli acquire incentive (reward) salience through learning (Berridge & Robinson, 1998; Chelazzi et al., 2014; Failing & Theeuwes, 2014). Behavior and neural responses to stimuli that are not associated with motivational value will stay consistent across time, but will be modulated to value-associated stimuli.[2]

H2a: Reward learning will have an effect on behavior during training, thus a Time x Block interaction will be observed in the reaction times (RTs) to targets in a spatial cuing task. The RT facilitation will be exclusive to reward, thus when splitting the RT data in half and by block type, the rewarding block of trials will show a modulation by time

[1] H1a and H1c comprise Aim 1, along with H1b which was addressed separately in Study 2.

[2] H2a and H2b comprise Aim 2.
[2] H2a and H2b comprise Aim 2.

(faster RTs on the second half), but not the neutral block of trials (Time x Block interaction) (Study 1).

H2b: Learning reward associations will have an effect on neural responses, thus a Time x Block interaction will be observed on the amplitudes of the P1 and N1 ERPs (Time x Block interaction) (Study 1). Increases in ERP amplitude will be due to reward, hence only the reward trials will show a modulation by time (larger ERP amplitudes on the second half compared to the first half of trials), but not the neutral trials (Study 1).

Aim 3. Reward salience is not limited to impacting solely exogenous (early) or endogenous (late) selection processes; value exerts its effect depending on the stage in processing that the value information is imparted. Hence value-driven effects on perceptual measures will depend on the type of stimulus that the motivational information is embedded in. If value is attached to spatial or early perceptual representation, effects of value will be evident prior to or at the stage of percept formation: value attached to cued locations will elicit changes in the amplitudes of P1 and N1.[3]

H3a: Reward attached to cues in a spatial cuing task will decrease RT and increase the amplitudes of cue-sensitive P1 and N1 ERPs but not the target-sensitive P2a (Study 1).

[3] Only H3a was investigated in Study 1; H3b and H3c were addressed separately in Study 2. All three predictions comprise Aim 3.

Study 1: Methods

Participants

59 undergraduate participants (45 females, 14 males), ages 18-32 (M = 20.6, SD = 3.4) were recruited via the University of South Florida Department of Psychology SONA subject pool. Eligible participants were self-reported right-handed, English-speaking with no reported neurological conditions or concussions, with normal or corrected-to-normal vision. Compensation for assessment included the possibility of winning one of two Amazon gift cards if they received one of two top scores in the sample for a given semester (first place received $30, second place received $10). Gift cards were disbursed to the winners at the end of a semester after the SONA pool had closed. The University of South Florida IRB approved all study protocols.

Stimuli and Design

Participants completed a spatial cuing task. In this task, two empty boxes flanking either side of a central fixation cross remained on the screen, and a symbol appeared in one of them. One box was always outlined pink and the other was blue; they remained in their respective visual fields for the entirety of a single trial. Before the symbol appeared, either one of the boxes would brighten or no brightening occurred for 200ms. Then a symbol, a target or nontarget, would appear and remain in one of the boxes for 200ms. The participant's task was to press the "4" key with their right hand on a 4-button response pad if they saw the target symbol appear in either of the boxes, or do nothing if they saw the nontarget symbol. Following the symbol's disappearance, the boxes and fixation cross remained on screen for 1300ms, followed

by feedback that appeared in place of the central cross for 1500ms, signaling the end of the trial. This feedback determined the type of block participants encountered (discussed below).

Targets were one of the symbols ϒ or ϳ, while nontargets were one of the symbols ⇜ or ⇝. The symbols within each stimulus category were equiprobable on each trial. All stimuli were presented against a black background, and the brightness of the pink and blue boxes were kept equivalent in experiment development using a photometer. An example of a trial sequence is shown on Figure 1.

There were two kinds of blocks distinguished by feedback: Reward and Neutral. On the Reward blocks, there was a potential reward or nonreward on each trial. On each trial in this block type, the blue box signified the potential for reward, and the pink box signified the potential for nonreward. Participants gained points if either a target or nontarget stimulus appeared in the blue (rewarding) box and if their response was correct; for this they were given feedback in the form of the text "+10 points" in green ink (Reward condition). They did not get a reward if the target or nontarget appeared in the pink (nonreward) box and if their response was correct, for which they were shown the text "+0 points" in red ink as feedback (Nonreward condition). Otherwise, they were given the feedback "Incorrect" in pink ink. All text feedback at the end of each trial was presented in the center, momentarily replacing the fixation cross. The designation of the blue box (reward location) was randomized between trials; thus, reward information was tied to the color of the box, not visual hemifield. Prior to the appearance of the target or nontarget, sometimes one of the boxes brightened, signified by the thickening of the box's outline for 200ms (Cued trial). If the target or nontarget stimulus appeared in the box that just brightened on that trial, this was a Valid condition. If it occurred in the opposite box, this

was an Invalid condition. Sometimes, no brightening occurred (also for 200ms); this was an Uncued condition.

On the Neutral blocks, there was no possibility of reward or nonreward. The stimuli and trials were identical as in the Rewarding block, except for the feedback, which was given in the form of accuracy ("Correct" in blue ink, or "Incorrect" in pink ink).

The inter-trial interval (ITI) was randomly jittered between 800 and 1200ms to avoid subject expectancy effects on the EEG. Participants saw 768 trials split into 8 blocks. Reward and Neutral blocks were interleaved, their order counterbalanced across participants. Prior to the experimental trials, participants performed practice trials when no EEG was recorded.

Procedure

Participants voluntarily signed up to take part in the study through the SONA online research participant pool. In the lab, consenting participants were fitted with the appropriate EEG net then led to the testing room where instructions for each task were shown and explained to them. Participants performed practice trials and the task as described above for no longer than 2.5 hours in a dimmed room. In between each block in the experiment, participants paused for a break. At the end of the experiment, participants were informed about the average points they earned across the blocks, and that they would be contacted if they won one of the gift cards at the end of the semester.

EEG Recording and Preprocessing

EEG was acquired through the 128-channel Geodesic Sensor Nets (Electrical Geodesics Inc., Eugene, OR). The data were referenced to the vertex electrode and filtered online between 0.1 and 100Hz at a sampling rate of 250Hz, then digitally filtered at 20Hz and segmented into 1000ms epochs (200ms before stimulus and 800ms after stimulus onset). Each

epoch was then screened for ocular and excess motor artifacts, and the cleaned data sorted by condition and averaged to create the ERP components for each of the 18 conditions from the 3 (Cue: Valid, Invalid, Uncued) x 2 (Stimulus: Target, Nontarget) x 3 (Value: Reward, Nonreward, Neutral) design. Average ERPs were baseline-corrected to the pre-stimulus period of 200ms for each participant. Individual components were then averaged across all participants to create the grand average to show the central tendency of the ERPs.

Participants with fewer than 20 good trials in any of the conditions were excluded from further analyses for behavior and ERPs. As there were 18 conditions, a high likelihood of excluding a large number of participants due to artifact rejection was expected. From the total sample of 59, two participants were dropped due to an incomplete recording, and 21 were subsequently dropped due to having fewer than 20 clean trials in at least one of the 18 original conditions. The final sample was composed of 36 individuals (26 females, 10 males) ages 18 to 32, (M = 20.0, SD = 3.0).

Study 1: Results

Behavior

Aims 1 and 3.

Trials whose RTs were beyond ±3*SD* for each participant were discarded (Mean proportion of total trials discarded per condition = 0.2%). Keypress speeds to the targets on the remaining trials were cast into a repeated-measures analysis of variance (rANOVA). There were no keypresses to nontarget stimuli, hence the model only included the factors Cue (Valid, Invalid, Uncued) and Value (Reward, Nonreward, Neutral) in a 3 x 3 rANOVA. There was a main effect of a main effect of Value, $F(2,34) = 22.44$, $p < 0.0001$, $\eta_p^2 = 0.57$, with faster RTs on both Reward and Neutral compared to Nonreward trials. There was no significant difference between Reward and Neutral stimuli. There was also a main effect of Cue, $F(2,34) = 150.67$, $p < .00001$, $\eta_p^2 = 0.90$, indicating RTs were faster to Valid-cued stimuli compared to Invalidly-cued stimuli (a validity advantage), and slowest RTs to Uncued. There was no significant difference between Invalids and Uncueds. Finally, there was a Value x Cue interaction, $F(2,34) = 4.62$, $p = 0.005$, $\eta_p^2 = 0.37$. (Table 1) Post-hoc comparisons using the Bonferroni correction revealed that the valid-invalid RT difference was largest on Reward trials ($M_D = 19.39$, $SEM_D = 3.4$, $p < 0.0001$), smaller on Neutral trials ($M_D = 10.54$, $SEM_D = 2.9$, $p = 0.003$), and nonsignificant on Nonreward trials ($p = 0.89$). This indicates that the validity advantage was greatest in the Reward condition (Figure 3). Pairwise *t*-tests comparing the validly-cued stimuli during Reward to all other conditions indicated that it was significantly faster than all other conditions (p's < 0.05) (Table 2).

Aim 2.

For the temporal analyses, the data was split into early and late halves to produce the Time factor. This was done separately for the Reward block and for the Neutral block. Again there were no keypresses to Nontargets, eliminating the Stimulus factor. Mean RTs for each participant (calculated over approximately 31 trials per condition in each participant) were then cast into a 2 (Time: Early, Late) x 2 (Block: Reward, Neutral) x 3 (Cue: Valid, Invalid, Uncued) rANOVA. There was a main effect of Cue as revealed before, $F(2,34) = 153.30$, $p < 0.0001$, $\eta_p^2 = 0.90$. There was a main effect of Time, $F(1,35) = 40.66$, $p < 0.0001$, $\eta_p^2 = 0.54$, indicating faster keypresses on the Late half of the trials compared to the Early half. There was also a Time x Cue interaction, $F(2,34) = 4.97$, $p = 0.013$, $\eta_p^2 = 0.23$. Post-hoc comparisons indicated that this effect of Time significant for all Cue types but was greatest for the Uncueds ($M_D = 25.36$, $SEM_D = 3.79$, $p < 0.0001$). There was also main effect of Block, $F(1,35) = 8.79$, $p = 0.005$, $\eta_p^2 = 0.20$, with faster keypresses on the Neutral block than on the Rewarding block. (Table 3). Mean RTs by Time and Block are shown on Figure 4.

An additional analysis was performed to verify the lack of interaction with Time in the original proposed rANOVA. It is possible that a median split of trials was not sufficient to capture any potential effects of block in the first or second half. The entire set of trials was split into fourths rather than halves, allowing for a more fine-grained analysis while allowing a sufficient number of observations per participant over which mean RTs could be calculated (approximately 16 trials per participant). This produced a factor called Bin (1, 2, 3, 4), and entered into a new rANOVA with the original factors Block (Reward, Neutral) and Cue (Valid, Invalid, Uncued). There was an effect of Block, $F(1,35) = 8.03$, $p = 0.008$, $\eta_p^2 = 0.19$, and an effect of Cue, $F(2,34) = 152.94$, $p < 0.0001$, $\eta_p^2 = 0.90$, as previously observed in the original

analysis. There was also a main effect of Bin, $F(3,33) = 17.24$, $p < 0.0001$, $\eta_p^2 = 0.61$, such that RTs in Bin 2 were faster than in Bin 1 ($M_D = 24.93$, $SEM_D = 4.22$, $p < 0.0001$), Bin 3 RTs were marginally slower than Bin 2 ($M_D = 8.45$, $SEM_D = 3.05$, $p = 0.053$), and Bins 3 and 4 were not significantly different ($p = 1.0$) (Table 4). Thus RTs decrease significantly from Bin 1 to 2, and marginally from 2 to 3, with no further decrease in the last bin of trials. There was a significant Bin x Cue interaction, $F(6,30) = 2.93$, $p = 0.023$, $\eta_p^2 = 0.37$. Post-hoc comparisons revealed that the Bin effect was driven by the Uncued trials (Bin 2 faster than Bin 1, $M_D = 17.24$, $SEM_D = 4.18$, $p = 0.001$, Bin 3 faster than Bin 2, $M_D = 16.42$, $SEM_D = ,3.78$, $p = 0.001$, Bins 3 and 4 not significantly different, $p = 1.0$). On the Valid and Invalid trials, the same Bin effect is observed from Bin 1 to 2, with the exception of no further significant decrease after Bin 2 (vs. Bin 3, p's > 0.5). Hence the RT decrease through the Bins levels off after Bin 3 but only on the Uncued trials. Crucially, no significant interactions with Bin and Block were observed, reflecting the finding of a lack of Time x Block interaction in the originally proposed analysis. Mean RTs by Time and Block are shown on Figure 5.

To ensure that the Value manipulation worked, an additional rANOVA was performed by adding Box Color (Blue, Pink) to the original proposed model above, resulting in a 2 (Time) x 2 (Block) x 3 (Cue) x 2 (Box Color) rANOVA. In the design, the meaning of the colors determined whether the block contained potential rewards/nonrewards or not, hence we would expect a significant Block x Box Color interaction. Specifically, there should be no RT difference between the Blue and Pink box in the Neutral blocks because both colors received the same accuracy feedback; but there should be a difference in the Rewarding block since correct responses to the Blue box were awarded points, while correct responses to the Pink box did not

receive points. This interaction would indicate changes due to feedback because the only difference between the blocks was the content of feedback shown (reward or accuracy).

In addition to the original effects of Time, Block, and Cue mentioned previously, there was also a main effect of Box Color, such that RTs to the Blue box were faster than to the Pink box overall, $F(1,35) = 33.61$, $p < 0.0001$, $\eta_p^2 = 0.49$ (Table 5). As predicted, there was a significant interaction of Box Color and Block, $F(1,35) = 27.40$, $p < 0.0001$, $\eta_p^2 = 0.44$), so that the difference between the Blue and Pink box was significant in both blocks but greater in the Rewarding block ($M_D = 24.44$, $SEM_D = 3.66$, $p < 0.0001$), and smaller in the Neutral block ($M_D = 7.21$, $SEM_D = 2.63$, $p = 0.01$). Box Color also interacted with Time, $F(1,35) = 9.88$, $p = 0.003$, $\eta_p^2 = 0.22$), such that the RT difference between the Blue and Pink boxes was greater during the Late half of the task ($M_D = 20.13$, $SEM_D = 3.36$, $p < 0.0001$) than in the Early half ($M_D = 22.52$, $SEM_D = 2.71$, $p < 0.0001$). Lastly, there was a significant Box Color x Cue interaction, $F(2,34) = 6.1$, $p = .006$, $\eta_p^2 = 0.26$; the difference between Blues and Pinks was greatest for Valid ($M_D = 22.45$, $SEM_D = 3.31$, $p < 0.0001$)) and smallest for Uncued stimuli ($M_D = 11.46$, $SEM_D = 2.96$, $p < 0.0001$). Mean RTs by Time, Block, and Box Color are shown in Figure 6.

ERPs

Aims 1 and 3.

Regions of interest (ROIs) for the ERPs were first selected based on the scalp distributions of the waveforms: lateral occipitotemporal leads for the P1 (110-180ms poststimulus) and N1 (190-250ms), and mediofrontal leads for the P2a (250-300ms). Electrode montages are shown in Figure 7.

3 (Cue: Valid, Invalid, Uncued) x 2 (Stimulus: Target, Nontarget) x 3 (Value: Reward, Nonreward, Neutral) rANOVAs were performed on the mean amplitudes extracted

from these spatiotemporal ROIs. This served as the omnibus rANOVA and was performed for the P1, N1, and P2a separately. Pairwise comparisons identifying significant contrasts within significant interactions were Bonferroni-corrected. Despite any absence of significant interactions with Value, effects of Cue (validity advantage) were compared for P1 and N1 analyses, and effects of Stimulus (target advantage) were compared for the P2a analyses at each level of the Value factor; these were also corrected with the Bonferroni method.

There was a main effect of Cue on P1 amplitude, $F(2,34) = 6.02$, $p = 0.006$, $\eta_p^2 = 0.26$, (Table 6), with P1 amplitudes to Valid being significantly larger than Invalid, and marginally larger than Uncued ($p = 0.08$). Invalid and Uncued were not significantly different. (Figure 8b). No significant Cue x Value interaction was observed, but the validity advantage that was observed in behavior was investigated in the P1. Planned pairwise comparisons examining the validity advantage (Valid larger than Invalid) on P1 amplitudes revealed that this effect was largest on Reward trials ($M_D = 0.61$, $SEM_D = 0.17$, $p = 0.001$), and nonsignificant on Nonreward and Neutral trials (p's > 0.1). (Figure 9, panel b).

For the N1, there was a main effect of Stimulus, with Targets eliciting a larger N1 compared to Nontargets, $F(1,35) = 30.28$, $p < 0.0001$, $\eta_p^2 = 0.46$. (Figure 8d). Stimulus interacted with Cue, with the Target-Nontarget difference being the largest for Invalid cues, $F(2,34) = 3.52$, $p = 0.041$, $\eta_p^2 = 0.17$ (Table 7). Planned comparisons examining the validity advantage on N1 amplitudes did not reveal significant advantages in any levels of the Value factor. (Figure 9, panel b).

For the P2a, there was a main effect of Stimulus, with Targets eliciting a larger P2a than Nontargets, $F(1,35) = 68.3$, $p < 0.0001$,h $\eta_p^2 = 0.66$. (Figure 8c). There was also a main effect of Value, $F(2,34) = 11.90$, $p < 0.0001$, $\eta_p^2 = 0.41$, with both Reward and Nonreward

eliciting a larger P2a compared to Neutral. (Reward and Nonreward were not significantly different from each other.) (Figure 8e). Lastly, there was a main effect of Cue, such that the P2a was larger for Invalids and Uncueds compared to Valids (Invalid and Uncued not significantly different from each other), $F(2,34) = 4.46$, $p = 0.019$, $\eta_p^2 = 0.21$ (Table 8) (Figure 8a). Planned comparisons of the target advantage (Target larger than Nontarget) revealed that the effect was largest on Reward trials ($M_D = 1.26$, $SEM_D = 0.18$, $p < 0.0001$), intermediate on Neutral trials ($M_D = 1.03$, $SEM_D = 0.14$, $p < 0.0001$), and smallest on Nonreward trials ($M_D = 0.81$, $SEM_D = 0.20$, $p < 0.0001$). (Figure 10, panel a).

Aim 2.

To examine the impact of reward-learning on the temporal course of the ERPs, individual mean ERP amplitudes were extracted from each trial for each subject. This was done for each trial before splitting the data into early (trials 1-384) and late halves (trials 385-768), to produce the Time factor. This procedure was done separately for the Reward block and for the Neutral block for each participant. Amplitudes were then cast into a repeated-measures ANOVA with Time (Early, Late) and Block (Reward, Neutral) as factors. Due to the large number of lost trials for the ERP averaging by the inclusion of the Time factor, and in order to identify whether Stimulus or Cue interacted with Time or Block, two separate rANOVAs were performed: one that included Time x Block x Cue (disregarded Stimulus), and another that only included Time x Block x Stimulus (disregarded Cue). Each of these rANOVAs was performed separately on the P1, N1, and P2a ERPs. Only subjects with at least 20 good trials per condition in each half were included, resulting in $N = 36$ included in the temporal analyses.

Time x Block x Cue rANOVA.

In addition to the Cue effect previously mentioned ($F(2,34) = 6.15$, $p = 0.005$, $\eta_p^2 = 0.27$), there was a marginal effect of Time on P1 amplitude, $F(1,35) = 3.61$, $p = 0.066$, $\eta_p^2 = 0.09$, with P1 on the Early half larger than on the Late half (Table 9) (Figure 11).

There was a marginal effect of Block on N1 amplitude, $F(1,35) = 3.31$, $p = 0.078$, $\eta_p^2 = 0.09$, with N1 during the Reward blocks marginally larger than on the Neutral blocks (Table 10) (Figure 11).

For the P2a, there was the aforementioned effect of Cue, $F(2,34) = 5.43$, $p = 0.009$, $\eta_p^2 = 0.24$. There was also an effect of Block $F(1,35) = 25.84$, $p < 0.0001$, $\eta_p^2 = 0.43$, with Reward eliciting a larger P2a than the Neutral block. The effect of Time approached significance, $F(1,35) = 3.61$, $p = 0.066$, $\eta_p^2 = 0.09$, with the P2a on the Late half marginally larger than on the Early half. Lastly, there was a significant Cue x Block x Time interaction, $F(2,34) = 5.35$, $p = 0.01$, $\eta_p^2 = 0.24$. (Table 11) Pairwise comparisons indicated that for the Control block, differences between Cue types were only present in the Early half (Invalid [$M_D = 0.83$, $SEM_D = 0.16$] and Uncued [$M_D = 0.77$, $SEM_D = 0.19$] both significantly larger than Valid, p's < 0.0001), but for the Rewarding block, no significant Cue effects occurred until the Late half (Invalid significantly larger than Valid ($M_D = 0.70$, $SEM_D = 0.24$, $p = 0.005$) and marginally larger than Uncued ($M_D = 0.50$, $SEM_D = 0.27$, $p = 0.07$). (Figure 11).

Time x Block x Stimulus rANOVA.

There was a Block x Stimulus interaction on the P1, $F(1,35) = 7.93$, $p = 0.008$, $\eta_p^2 = 0.19$, (Table 12). Post-hoc comparisons showed that P1 amplitude was larger to Targets compared to Nontargets only in the Neutral block ($M_D = 0.23$, $SEM_D = 0.09$, $p = 0.01$), not the Reward block ($p = 0.18$). There was a marginal effect of Time, $F(1,35) = 3.0$, $p = 0.091$, $\eta_p^2 =$

0.08, with P1 amplitude being marginally larger in the Early half compared to the Late half. (Figure 12).

For the N1, there was a main effect of Stimulus as previously found, with Targets being more negative than Nontargets, $F(1,35) = 28.46$, $p < 0.0001$, $\eta_p^2 = 0.45$ (Table 13). Stimulus interacted with Block, $F(1,35) = 5.61$, $p = 0.023$, $\eta_p^2 = 0.14$, such that the difference between Target and Nontarget was larger in the Reward block ($M_D = 0.59$, $SEM_D = 0.10$, $p < 0.0001$) than in the Neutral block ($M_D = 0.29$, $SEM_D = 0.11$, $p = 0.01$). There were no interactions with Time. (Figure 12).

For the P2a, there was a main effect of Stimulus as previously found, with Targets being larger than Nontargets, $F(1,35) = 75.22$, $p < 0.0001$, $\eta_p^2 = 0.68$ (Table 14). Stimulus had a marginally significant interaction with Time, $F(1,35) = 2.91$, $p = 0.097$, $\eta_p^2 = 0.08$; post-hoc comparisons showed that the Target-Nontarget difference was larger in the Late half ($M_D = 1.14$, $SEM_D = 0.14$, $p < 0.0001$) compared to the Early half ($M_D = 0.84$, $SEM_D = 0.15$, $p < 0.0001$). There was also a main effect of Block, with Reward eliciting a larger P2a than the Neutral block, $F(1,35) = 29.32$, $p < 0.0001$, $\eta_p^2 = 0.46$. (Figure 12).

Study 1: Discussion

Aim 1 states that perceptual representation and instructed relevance are distinct cognitive operations, hence their neural indices will possess distinct spatio-temporal distributions. In Study 1, P1 and N1 ERP indices of sensory representation were predicted to be larger and behavior fastest to validly-cued stimuli compared to uncued stimuli, regardless of whether the imperative stimuli were targets or nontargets (H1a). This hypothesis was partially supported. Behaviorally, target keypresses were fastest to validly-cued stimuli; RTs were also faster on validly-cued stimuli when compared to invalidly-cued stimuli (a validity effect), and both valid- and invalidly-cued stimuli elicited faster keypresses relative to stimuli that were not cued (an alerting effect). For the neural indices, P1 amplitude was largest to cued stimuli regardless of whether the imperative stimuli were targets or nontargets. The N1 did not show the same pattern; instead, cue type interacted with stimulus type, such that targets elicited a larger N1 compared to nontargets especially when they were invalidly-cued. A puzzling effect, but one that might be explained by the fact that targets elicited a larger N1 overall. Although the P1 and N1 typically show the same enhancements to cued stimuli, the difference in results in the current study could lie in the distinction between the attentional mechanisms indexed by each one: P1 being a measure of suppression of unattended input prior to the onset of the imperative stimulus, and N1 a measure of enhancement of input at an already-attended location (Hillyard & Anllo-Vento, 1998; Luck et al., 1990). That the N1 effect is strongest on stimuli occurring on the other side as a cued location (invalidly-cued trials) is not likely due to inhibition of return (IOR), as IOR effects are maximal at cue-target intervals of 500-1000ms (Posner & Cohen, 1984). In the

current study, the cue-target interval was 200ms, less than the minimum interval a possible IOR. More importantly, any cue-induced N1 enhancement should not have been expected to occur in the current design, as it is not typically found in go/no-go cuing designs such as Study 1, but are found more reliably in two-alternative forced-choice tasks (Hillyard, Vogel, & Luck, 1998).

While the early ERPs index early perceptual representation prior to percept formation (in the case of study 1, the sensory enhancement given by the brightening cue prior to the appearance of an imperative stimulus), the P2a ERP indexes instructed relevance, which occurs after a stimulus percept is formed. This was predicted to be larger to targets compared nontargets in study 1, regardless of whether they were cued or uncued (H1c), which was supported in the current study. There was also a small effect of cue, so that invalidly- or un-cued stimuli elicited a larger P2a compared to validly-cued stimuli. Hence both hypotheses of Aim 1 were mostly supported by Study 1: A cue validity effect in the behavioral and P1 ERP measures of early perceptual enhancement prior to the appearance of the imperative stimulus, and a target effect in the P2a ERP index of instructional relevance.

For Aim 2, there were two key hypotheses being tested in Study 1, based on the idea that responses to stimuli that acquire reward value should be modulated over time, while responses to neutral stimuli should not, signifying reward-based learning, an attachment of incentive salience (Berridge, 2007; Berridge & Robinson, 1998). H2a hypothesized that a Block x Time interaction would be observed in the RTs to targets, such that only the Reward block would show a modulation of RTs over time, and not the Neutral block where no motivational values are assumed to be coded. This was not supported by the results. While there was a main effect of Time on behavior, it did not interact with Block: although RTs were generally faster as the task progressed, indicating perceptual learning and habituation to task demands, this occurred

regardless of whether the prevailing context was a reward-present or reward-absent (neutral) block. This was also true even after splitting the temporal factor into more observations. Even though no effects of time were observed, there was still an interactive effect of block and box color, signifying that participants were learning to associate reward values to the blue boxes and nonreward values to the pink boxes, but only on the rewarding blocks. This was indicated by the presence of an RT difference between blue and pink boxes on the reward blocks, but a lack thereof on the neutral blocks. While not originally proposed, this finding suggests that reward-based learning was taking place, consistent with accounts that employ feedback to manipulate reward information but keep stimulus feature (color, shape) constant (Anderson, Laurent, & Yantis, 2011b; Failing & Theeuwes, 2014).

The second hypothesis of Aim 2 (H2b) had an analogous prediction for Study 1, that a Block x Time interaction would be observed in the P1 and N1 ERPs. No interactions with Time and Block were observed in the P1 or N1. However, the interaction of cue, block type, and time did have an effect on the P2a ERP. Here, cue effects varied in the early half of the task for the neutral block where no reward information was present, but cue effects moved in the later half for the potentially rewarding block. That this occurred only in the later ERP index of instructed relevance might explain why no interaction effects of time and reward were observed in the behavior. Thus the interim conclusion for Aim 2 was that reward-based learning did occur, but did not manifest until the level of stimulus evaluation as indexed by the P2a.

Aim 3 states that the effect of reward value on processing would depend on the process/stage in which the motivational information was imparted during learning. In Study 1, reward value was attached to the color of the cue (box); hence box color served as a reward cue in addition to the actual perceptual cue (the brightening of the box), information that was given

prior to the appearance of the stimulus. Hence it was proposed that rewarded cues would decrease RTs and increase the amplitudes of the P1 and N1 ERPs as they would to perceptual cues, but that no effects would be observed in the P2a ERP (H3a). This hypothesis was partially supported. Behavioral results showed an interaction of value with cue, such that the cue validity effect was largest on reward trials, suggesting that the perceptual advantage was enhanced when the possibility of reward was present. This validity advantage was echoed in the P1 ERP, where although in the absence of a significant interaction of value and cue, the cue validity effect was still largest on reward trials. Of note is the effect of value on the P2a, such that both nonrewarded and rewarded stimuli enhanced P2a amplitude relative to neutral stimuli. Further analyses with block type as a factor showed that this is explained by an effect of context: when there was a possibility for reward during a block, the P2a was significantly enhanced, regardless of whether a reward or nonreward was delivered. But when there was no reward information available (neutral block), the P2a was much smaller.

To sum up the findings for Aims 2 and 3 together, reward-associated cues produced early attentional allocation as seen in the facilitation of RTs and P1 ERP to locations that signified reward. However, this effect did not change over time. Meanwhile, reward relevance was maintained across time as indexed by the P2a effect of reward context, such that any stimulus (regardless of whether it was an instructed target or nontarget) appearing in a location that signaled the possibility for any amount of reward, was deemed relevant, similar to instructed targets.

The current investigation tests the idea that reward-driven effects are limited to the process being imbued with reward information. In Study 1, reward information was conveyed by spatial cues, thus producing early attentional allocation prior to the appearance of the target-

defining stimuli. It was not possible to introduce reward information at the target-selection level, hence Study 2 was performed. Study 2 used a target detection task to endow spatial locations or object shapes with reward, permitting the comparison of target-defining features (location or object) with reward-associated features (location or object) on the ERPs. Thus, Study 1 permitted the investigation of reward's effects on selection processes prior to percept formation (exogenous attention), while Study 2 tests reward's effects after percept formation (endogenous attention).

Study 2: Aims

Following are the general aims introduced in Study 1, but including only the predictions specific to Study 2.

Aim 1. Perceptual representation and instructed relevance are distinct cognitive operations, thus their neural indices will possess distinct spatio-temporal distributions. Perceptual representation will engage the posterior attention system, eliciting changes in the P1, N1, and N2b ERPs, while instructed relevance will engage the anterior system, as indexed by the P2a, replicating previous work (Luck, Heinze, Mangun, & Hillyard, 1990; Potts & Tucker, 2001).[4]

H1b: The P1, N1, and dorsal N2b indices of spatial representation will be larger during spatial selection. The ventral N2b, indexing object features, will be larger during stimulus shape selection. Thus, the P1, N1, and dorsal N2b will be more negative in the location target detection task, while the ventral N2b will be more negative in the object target detection task (Task x ROI interaction) (Study 2).

H1c: The P2a, indexing instructed relevance, will be larger to instructed targets than nontargets (main effect of Stimulus), regardless of task (Study 2).

Aim 2. Acquiring reward value associations produces a change in behavior over time, hence stimuli acquire incentive (reward) salience through learning (Berridge & Robinson, 1998; Chelazzi et al., 2014; Failing & Theeuwes, 2014). Behavior and neural responses to stimuli that

[4] H1b and H1c comprise Aim 1, along with H1a which was addressed separately in Study 1.

are not associated with motivational value will stay consistent across time, but will be modulated to value-associated stimuli.[5]

H2b: Learning reward associations will have an effect on neural responses, thus a Time x Block interaction will be observed on the amplitudes of the P1, N1, dorsal N2b, ventral N2b (Time x Trial Type x Task interaction), and P2a ERPs (Time x Trial Type interaction) (Study 2). Increases in ERP amplitude will be due to reward, hence only the reward trials will show a modulation by time (larger ERP amplitudes on the second half compared to the first half of trials), but not the nontarget trials (Study 2).

Aim 3. Reward salience is not limited to impacting solely exogenous (early) or endogenous (late) selection processes; value exerts its effect depending on the stage in processing that the value information is imparted. Hence value-driven effects on perceptual measures will depend on the type of stimulus that the motivational information is embedded in. Value attached to spatial locations will elicit changes in the amplitudes of the dorsal N2b ERP index of spatial selection, but not the ventral N2b ERP index of object categorization, while value embedded in stimulus shape will modulate the amplitude of ventral N2b but not of the P1, N1, or dorsal N2b. Finally, value conveyed at the level of target selection will enhance the P2a index of relevance evaluation, regardless of the reward-associated stimulus feature.[6]

H3b: Rewarded locations will elicit larger P1, N1, and dorsal N2b but will not produce effects in the ventral N2b. Rewarded objects will elicit larger ventral N2b but no effects in the P1, N1, and dorsal N2b (Stimulus x Task interaction) (Study 2).

[5] H2b is part of Aim 2, along with H2a which was addressed separately in Study 1.

[6] Only H3b and H3c were addressed in Study 2; H3a was investigated in Study 1. All three predictions comprise Aim 3.

H3c: Reward that is embedded at the level of target evaluation but is not an instructed target will enhance P2a amplitude relative to nontargets. P2a will be larger to rewarded nontargets relative to nonrewarded nontargets, regardless of block type (Main effect of Stimulus) (Study 2).

Study 2: Methods

Participants

68 undergraduate participants (50 females, 18 males), ages 18-31 (M = 19.4, SD = 2.3) were recruited through the University of South Florida Department of Psychology SONA subject pool. Eligible participants followed the same criteria and were subject to the same gift card payment rules as in Study 1. This was a separate sample from Study 1.

Stimuli and Design

Participants performed a target detection task. In this task, four boxes remained on the screen, one on each corner of the screen equidistant from a central fixation dot. On each trial, one of four symbols (X, T, □, □) appeared in any of the boxes. Two kinds of blocks determined the task of the participant: selection by Object, and selection by Location. On Object blocks, one of the four symbols was designated as the target. Participants were instructed to press the "4" key on a 4-button response pad any time the target object appeared in any of the four boxes (Target trial). Another symbol was assigned as the non-target rewarded object. Whenever this symbol appeared, participants were instructed not to press a key, but were informed that a monetary reward would be delivered on that trial (Reward trial). The two remaining symbols were designated as non-targets, for which the participant was instructed not to press any key (Nontarget trial). On Location blocks, one of the four boxes was designated as the target location. Participants were instructed to press the "4" key whenever any of the symbols appeared in this location (Target trial). Another location was designated as the non-target rewarded location. Whenever any symbol appeared in this location, participants were instructed not to

press a key, and were informed that a monetary reward would be delivered on that trial (Reward trial). On all other trials, the two remaining boxes served as non-targets, which the participant was instructed not to press any key (Nontarget trial).

The inter-trial interval (ITI) was randomly jittered between 800 and 1200ms, signaling the start of the trial. The symbol stimulus appeared and remained on-screen for 150ms, then disappeared for 500ms. Text feedback was then displayed on screen in place of the central fixation dot for 1500ms. Feedback could be one of the following depending on the trial type: "Correct" in blue ink on target-object or target-location trials where the participant pressed the "4" key, or "+10 points" in green ink on reward trials where the participant did not press a key. On all other trials, the text "Incorrect" in red ink was displayed. The four boxes never disappeared throughout a block of trials. An example of a trial sequence is shown in Figure 2.

The object and location on any trial was equiprobable and selected randomly without replacement from a pool of trial types. On Object blocks, the location in which each object type appeared (Target, Reward, Nontarget) was randomly selected. On Location blocks, the object symbol contained by the location on a certain trial type (Target, Reward, Nontarget) was chosen randomly. Trial types were counterbalanced such that a participant did not have the same target-location or target-object appear as the rewarded-location or object on the subsequent block.

Participants performed two Object blocks and two Location blocks in alternation. Halfway through the experiment, new locations and objects were selected as targets and rewarded non-targets. Hence each participant performed four blocks total, with a different target and different rewarded nontarget on the third and fourth blocks. There were 336 trials per block type, for a total of 672 trials per participant. A break was enforced every 84 trials. Task order was counterbalanced across participants.

Procedure

Study 2 followed the same recruitment and EEG procedure as Study 1.

EEG Recording and Preprocessing

EEG was recorded and preprocessed using the same settings as in Study 1, with the exception of the conditions for creating the epochs. There were six segment types, corresponding to one of the cells in the 2 (Task: Object, Location) x 3 (Stimulus: Target, Nontarget, Reward) design.

Participants with fewer than 20 good trials per condition were excluded from further analyses for behavior and ERPs. From the total sample of 68, one participant was excluded due to an incomplete EEG recording, and two were subsequently dropped due to an insufficient number of good trials in at least one of the 6 original conditions. Unlike Study 1 which had 18 original conditions and thus a higher likelihood of excluding a participant, Study 2 only had 6, hence the vast difference in the magnitude of data loss. The final sample for Study 2 was composed of 65 individuals (48 females, 17 males) ages 18 to 31, (M = 19.5, SD = 2.3).

Study 2: Results

Behavior

Trials whose RTs exceeded ±3*SD* for each participant were discarded (mean proportion of total trials discarded per condition = 0.1%). There were no keypresses to nontargets, hence keypress speeds to the targets on the Object and Location tasks, respectively, were compared using a paired-samples *t*-test, which showed that target RTs during the Location task were significantly faster than on the Object task, $t(64) = 43.3$, $p < 0.0001$. (Figure 13)

ERPs

Aims 1 and 3.

For the ERP analyses, only trials where the behaviorally accurate response was provided were included (i.e. pressed key to target stimuli, or did not press key to nontarget or rewarded nontarget stimuli). Based on the distributions of the waveforms, ROIs were selected for the P1 (lateral occipitotemporal leads from 90-140ms poststimulus) and N1 (lateral occipitotemporal leads from 150-200ms) and the following ERPs in the 150-300ms poststimulus time window: centroparietal leads for the dorsal N2b, lateral temporal leads for the ventral N2b, and mediofrontal leads for the P2a. (Figure 14).

rANOVAs were performed for each of the mean amplitudes of the above ERPs as follows. Since Targets and Rewarded nontargets were the effects of primary focus, difference waves were first calculated for each participant by subtracting Nontarget amplitudes from Target and Reward amplitudes separately, resulting in Target Effect and Reward Effect as levels of a Stimulus factor. This was submitted into a 2 (Task: Location, Object) x 2 (Stimulus: Target Effect,

Reward Effect) rANOVA for the difference waves for the P2a, P1, and N1 ERPs. For the N2b analyses, scalp distribution ROI was entered as an additional factor called, resulting in a 2 (ROI: Dorsal, Ventral) x 2 (Task) x 2 (Stimulus) rANOVA for the N2b.

The latencies of the target P2a and N2b difference waves were also compared between the Location and Object tasks, permitting a direct comparison of results to Potts & Tucker's (2001) study. Latencies of the peaks of the raw conditions (Target, Nontarget, Reward) were first extracted for each participant prior to performing the subtractions for the difference waves. No specific predictions were made for the latencies with respect to reward effects; hence the latency analyses beyond the Task differences that were expected based on Potts & Tucker's study are exploratory. Due to latency differences between the two tasks (see *Latency analyses* below), time windows for N2b mean amplitudes were adjusted by task before the rANOVAs on N2b amplitude was conducted: 150-220ms for the Location task, and 230-300ms for the Object task.

Amplitude analyses.

The Task x Stimulus rANOVA (Table 15) revealed a significant effect of Stimulus on P2a amplitude, $F(1,64) = 49.97$, $p < 0.0001$, $\eta_p^2 = 0.44$, with the Target Effect being larger than the Reward Effect regardless of task. (Figure 15a)

For N2b amplitudes, the ROI x Task x Stimulus rANOVA (Table 16) revealed a main effect of Stimulus, $F(1,64) = 64.01$, $p < 0.0001$, $\eta_p^2 = 0.50$, with the Target Effect eliciting a larger N2b. There was also an ROI x Task interaction, $F(1,64) = 10.83$, $p = 0.002$, $\eta_p^2 = 0.15$, with the N2b being larger (more negative) over Ventral leads than Dorsal leads in the Object task regardless of Stimulus. Crucially, there was an ROI x Task x Stimulus interaction, $F(1,64) = 19.7$, $p < 0.0001$, $\eta_p^2 = 0.24$, with the Target Effect being larger than the Reward Effect for the Dorsal ROI during the Location Task ($M_D = 1.09$, $SEM_D = 0.18$, $p < 0.0001$) (Figure 15b), but

larger over the Ventral ROI during the Object task (M_D = 1.15, SEM_D = 0.14, $p < 0.0001$). (Figure 15c).

For P1 amplitudes, no significant effects or interactions were observed (Table 17). There was a marginal main effect of Stimulus, $F(1,64) = 3.83$, $p = 0.06$, $\eta_p^2 = 0.06$, whereby Targets elicited a marginally larger P1 effect than Rewards regardless of Task. (Figure 15d).

For N1 amplitudes, the Task x Stimulus rANOVA (Table 18) revealed a main effect of Task, $F(1,64) = 11.73$, $p = 0.001$, $\eta_p^2 = 0.16$, with the Location task eliciting a larger (more negative-going) N1 than the Object task. There was also a main effect of Stimulus, $F(1,64) = 16.59$, $p < 0.0001$, $\eta_p^2 = 0.21$, such that the Target Effect was larger than the Reward Effect. Lastly, there was a Task x Stimulus interaction, $F(1,64) = 26.53$, $p < 0.0001$, $\eta_p^2 = 0.29$, where the Location task elicited a larger N1 than the Object task but only for the Target Effect (M_D = 0.84, SEM_D = 0.16, $p < 0.0001$). (Figure 15d).

Latency analyses.

The Task x Stimulus rANOVA on P2a peak latency (Table 19) revealed a main effect of Task, such that P2a peak was earlier for the Location task than the Object task regardless of Stimulus, $F(1,64) = 32.31$, $p < 0.0001$, $\eta_p^2 = 0.34$ (M_D = 22.52, SEM_D = 3.96). There was a main effect of Stimulus, $F(1,64) = 8.44$, $p = 0.005$, $\eta_p^2 = 0.12$, whereby the Reward Effect P2a occurred earlier than the Target Effect (M_D = 10.54, SEM_D = 3.63). There was also a Task x Stimulus interaction, $F(1,64) = 108.90$, $p < 0.0001$, $\eta_p^2 = 0.63$, such that P2a peak was earlier during the Location task but especially for the Target Effect (M_D = 58.7, SEM_D = 3.16, $p < 0.0001$). Due to the lack of a discernible peak of the Reward condition in the grand-average difference waveforms, any effects or interactions with the Stimulus factor, specifically the

Reward condition, are likely due to noise. Hence reporting will be limited to comparisons Target latencies. (Figure 15a).

Time x ROI x Task x Stimulus rANOVAs on N2b latency (Table 20) revealed a main effect of Stimulus, $F(1,64) = 16.71$, $p < 0.0001$, $\eta_p^2 = 0.21$, with the Reward Effect occurring earlier ($M_D = 7.30$, $SEM_D = 1.79$). There was also an ROI x Task interaction, $F(1,64) = 38.19$, $p < 0.0001$, $\eta_p^2 = 0.37$, where peak latencies during the Object task were faster than the Location task over the Dorsal ROI ($M_D = 6.92$, $SEM_D = 2.34$, $p = 0.005$), but faster during the Location task compared to the Object task over the Ventral ROI ($M_D = 12.72$, $SEM_D = 2.20$, $p < 0.0001$) regardless of stimulus. (Figure 15b, 15c).

Aim 2.

To examine the impact of reward-learning on the temporal course of the ERPs, individual mean ERP amplitudes were extracted from each trial. This was done for each trial before splitting the data into early (trials 1-336) and late halves (trials 337-672), to produce the Time factor with levels Early and Late. This procedure was performed for Target, Nontarget, and Reward trials for each participant separately prior to performing Nontarget subtractions to obtain Target and Reward difference waves as described above. This procedure was performed separately for the P2a and N2b analyses. Amplitudes were cast into a Time (Early, Late) x Task (Location, Object) x Stimulus (Reward Effect, Target Effect) as factors for the P2a, and for the N2b, the same model was used with the addition of ROI (Dorsal, Ventral). Only subjects with at least 20 good trials per condition in each half were included, resulting in $N = 47$ included in the temporal analyses. Due to the high number of trials needed to elicit reliable P1 and N1 ERPs being more than the number of possible trials on each half in the current design, this analysis was not performed on the P1 and N1 amplitudes.

The Time x Task x Stimulus rANOVA on P2a amplitudes (Table 21) revealed no significant effects or interactions with Time. There was a main effect of Stimulus that was previously found, $F(1,46) = 64.62$, $p < 0.0001$, $\eta_p^2 = 0.58$). Pairwise comparisons of Time or Stimulus yielded no significant comparisons for Time x Stimulus or Time x Task x Stimulus at the Reward Effect level (p's > 0.1). (Figure 16)

For the N2b's, the ROI x Task x Stimulus rANOVA revealed no significant effects or interactions of Time (Table 22). There was a main effect of ROI, in which ventral N2b amplitude was more negative than Dorsal N2b regardless of stimulus, $F(1,46) = 5.48$, $p = 0.024$, $\eta_p^2 = 0.11$). Similar to previous findings before accounting for time, there was a main effect of Stimulus ($F(1,46) = 46.45$, $p < 0.0001$, $\eta_p^2 = 0.50$) as well as interactions of ROI x Task ($F(1,46) = 10.08$, $p = 0.003$, $\eta_p^2 = 0.18$) and of ROI x Task x Stimulus ($F(1,46) = 19.95$, $p < 0.0001$, $\eta_p^2 = 0.30$), Pairwise comparisons of Time produced no significant effects in Time x Stimulus, Time x Task x Stimulus, or Time x ROI x Stimulus (p's > 0.1). (Figure 16)

Study 2: Discussion

Aim 1 stated that perceptual representation would engage the posterior attention system, eliciting changes in the P1, N1, and N2b ERPs, but that this would change depending on the type of stimulus feature being selected: P1, N1, and dorsal N2b if the target feature being selected is a spatial location, and ventral N2b if the target feature is object shape (H1b). This hypothesis was mostly supported in Study 2: enhanced N1 and dorsal N2b during the spatial selection (location) block and enhanced ventral N2b during the shape selection (object) block. Aim 1 also hypothesized that the P2a would exhibit a target effect regardless of task (H1c), which was also supported. A replication of Potts & Tucker (2001), these findings support the idea that relevance enhances perceptual representation over posterior sensory cortex depending on the feature being selected, but engages frontal mechanisms of control regardless of the type of selection being made (Braver & Cohen, 2000; Buschman & Miller, 2007; Corbetta et al., 1991). It was also found that RTs to targets were faster and P2a peak earlier during the location task as compared with the object task, a replication of Potts & Tucker (2001). Selection by location was faster and easier because it was simple change detection, while object selection required fine discrimination of shape prior to a perceptual decision made, a process that lasts longer. This is consistent with the evidence of perceptual enhancements over posterior sensory cortex being induced by specific stimulus features due to selective attention (Buschman & Miller, 2007; Corbetta et al., 1991), and more specifically to inferior-temporal (IT) neurons whose timing and eliciting properties closely mirror those of the N2 ERP component (Chelazzi, Miller, Duncan, & Desimone, 2001; Luck, Girelli, McDermott, & Ford, 1997).

Aim 2 posited that neural responses to reward-related stimuli would be modulated across time, thus an interactive effect of time and stimulus should be observed in the dorsal N2b to rewarded stimuli during the location task, but in the ventral N2b to rewarded stimuli during the object task, and in the P2a across tasks. No effects of time and stimulus were observed in any of the ERP indices. One potential reason is that a median split of the early and late halves was not sensitive enough to modulations by reward association across time. Studies that bin trials into fixed or quantile amounts might be more sensitive measures of any time-sensitive learning effects (Failing & Theeuwes, 2014; Raymond & O'Brien, 2009). However, the more likely reason for the null findings of time could involve the findings pertaining to Aim 3, which stated that reward would have analogous effects as instruction: rewarded locations would elicit a larger P1, N1, and dorsal N2b, rewarded object shapes would produce and enhanced ventral N2b (H3b), and rewarded stimuli regardless of task would elicit a larger P2a (H3c). No reward effects were observed in any of these ERP indices.

While instructed stimulus features were selected as predicted in Study 2, attracting increased cortical representation (Aim 1), rewarded stimulus features did not produce any effects overall, nor were these effects modulated by time (Aims 2 and 3). Instruction, even when presented in the same context as reward, still enhanced perceptual representation. Rewarded nontargets were not significantly different from nonrewarded nontargets, thus reward did not enhance perceptual representations to the same extent as instruction. One possibility for this is that no percept of the rewarded stimuli was formed. If true, either reward did not engage mechanisms of relevance at all, or instruction prevented any potential percept of reward from being formed at all. The former case is not likely to be true; reward effects on indices of stimulus relevance, especially those of the anterior attention system, are robust, even when the selection

task is passive (Potts, Martin, Burton, & Montague, 2006), or performed separately from the context in which reward values were learned (Rossi et al., 2017). (For a review of the Reward Positivity/RewP, see (Proudfit, 2015). Therefore it is more likely that instruction via the target-defining features prevented a percept from the reward-associated features from being formed in the current design.

General Discussion

The current study tests the idea that effects of reward attachment will be limited to the process (or stage) in which this reward information was imbued: if attached prior to percept formation, effects must be evident in spatial representation, while attachment after percept formation should lead to changes in stimulus categorization and relevance evaluation. Two studies manipulated the process where motivational information was introduced: Study 1 (spatial cuing) investigated selection effects prior to percept formation by endowing reward value in cued locations, while Study 2 (target detection) tested selection effects after percept formation by imbuing reward value on instructed targets.

Reward-driven Attention

Study 1 conveyed reward information in the cue, leading to perceptual enhancements in behavior and neural indices. Its findings suggest that motivational (reward) information interacted with perceptual information to attract enhanced processing resources over and above that recruited by perceptual information absent reward. These results supported the study's prediction that reward-driven selection would impact the stage of early perceptual representation when reward is attached to the cues. Reward interacted with spatial cue information in the same context to further facilitate processing of imperative stimuli when they were validly-cued, a finding consistent with previous cuing designs that imbued reward in a separate value learning task (Failing & Theeuwes, 2014; MacLean & Giesbrecht, 2015a). The rapid reward-driven effects demonstrated in Study 1 are consistent with the capture-like properties of exogenous

attention (Näätänen, 1992) as demonstrated in cuing tasks absent any reward information (Eriksen & St James, 1986; Posner et al., 1980).

It can be concluded that Study 1 was able to activate both exogenous and endogenous mechanisms of selection. Neurally, Study 1's reward effects on the P1 ERP index of early perceptual representation over sensory cortex were consistent with posterior cortical recruitment by exogenous attention (Buschman & Miller, 2007; Katsuki & Constantinidis, 2014; Posner & Petersen, 1990). As for the P2a index of the anterior attention system (Posner & Petersen, 1990; Potts & Tucker, 2001), it was found to be sensitive to reward context, being larger to both reward and nonreward compared to neutral stimuli. This finding was further supported by the effect of block, such that the P2a was larger during the potentially rewarding block compared to the neutral block. Note that the neutral block still required attention to relevance, as targets were still task-relevant; the only difference between the two blocks was the feedback. It thus appears that reward context recruited frontal mechanisms of cognitive control (Braver & Cohen, 2000; Miller & Cohen, 2001) to a greater extent than a context absent any reward information but still requiring evaluation of task-relevant features. Hence in Study 1, the P2a effect can be interpreted as indexing general relevance due to value in both domains, rather than just the reward domain.

The results of Study 1 are also consistent with accounts of reward information as needing to interact with low-level stimulus features to produce any enhanced perceptual recruitment, so that behavior can be biased towards the optimal response criterion (Hickey, Chelazzi, & Theeuwes, 2010; Rossi et al., 2017). In support of this, previous work has found value-driven P1 enhancements that were specific to reward relative to loss, or high-reward compared to low-reward, suggesting that the early attentional allocation produced by value-associated items is biased towards the more optimal criterion (Hickey et al., 2010; Luque et al.,

2017; MacLean & Giesbrecht, 2015b). In this regard, reward-driven salience behaves similarly to feature-based attention: just as attention to specific features such as spatial location, movement, or color attracts increased neural processing resources in those channels, so can reward, or any motivational information including loss. Indeed, Rossi et al. (2017) found that early ERP effects of learned motivational (loss) values were generalized to unfamiliar but similar shapes in a separate context, supporting a feature-based account of motivational salience. But this argument does not hold true in Study 2, which signaled reward information through the imperative stimulus, a different stage in processing than in Study 1.

As predicted, Study 2 demonstrated target-defined location- and object-selection effects in dorsal and ventral ERP indices, and general frontal selection regardless of the target feature being selected (Potts & Tucker, 2001). This suggests that instructional relevance recruited mechanisms of endogenous attention by biasing the sensory representations corresponding to these selected features—dorsally for spatial representations, ventrally for object representations—while goal representations were maintained in frontal cortex (Buschman & Miller, 2007; Miller & Cohen, 2001; Posner & Petersen, 1990). The target detection task thus successfully activated the fronto-parietal network (Katsuki & Constantinidis, 2014), leading to the biasing of the appropriate sensory pathways that are behaviorally relevant (Braver & Cohen, 2000).

Though Study 2 demonstrated the predicted target-driven selection effects, no effects of reward-associated selection were observed. It can be argued that reward did not (and cannot) recruit the same mechanisms of endogenous/top-down relevance in the fronto-parietal network at all, but such an explanation would be too simplistic. Previous work has shown robust effects of

reward over frontal cortex when value information is conveyed by symbolic stimuli during learning (Potts et al., 2006; Proudfit, 2015), so this possibility is unlikely.

Instead, the null reward effects in Study 2 could more likely be due to a crucial design issue, specifically that of competing reward and target information in the same block, leading to target information "crowding out" any potential reward effect. If this is true, future work should present nontarget and target trials in their own block, and nontarget and reward trials in a separate block. This would directly test prioritization, or the ability of stimuli or stimulus features to attract increased processing resources, even when presented in isolation (Rossi et al., 2017). This was not the case in the current design, which presented reward and instructional relevance in the same context. Of note, similar target-detection designs that have found reward effects emphasized reward-associated selection in their own block, potentially prohibiting any interference by target-defined selection (Potts et al., 2006).

An alternative route that could address the potential interference issue would be to use a two-phase paradigm, in which reward values are first acquired in a choice reinforcement-learning task, followed by a perceptual judgment task (such as target detection in Study 2) in which stimuli from the first phase are presented but their reward values are no longer task-relevant. By administering a reward-learning task (value relevant, perceptual instruction irrelevant) followed by an orthogonal perceptual task (value irrelevant, perceptual instruction relevant), the reward and instruction contexts are kept separate. While early attention ERP indices during the orthogonal perceptual test have been shown to be sensitive to learned reward values, even a week after reward-learning (Luque et al., 2017; MacLean & Giesbrecht, 2015b), there are documented enhancements specific to reward (gain) information in later ERP indices of

selection such as the P3 (Rossi et al., 2017). The design of Study 2 did not separate the reward and instruction contexts in the same way, hence no reward effects were observed.

Mapping Reward Associations through Incentive Salience

It was hypothesized that reward-associated stimuli would acquire incentive salience (reward values) through time, while neutral stimuli would not (Berridge & Robinson, 1998). No robust modulation by time was observed in the neural indices in the current investigation (with the exception of Study 1, which demonstrated time-sensitive changes in the P2a index of target relevance, but only when combined with cue information), hence the current hypothesis was not supported. This suggests that no incentive salience was attached to the reward-associated stimuli in the task, hence no learning occurred. In the case of Study 1, one possibility is that as a result of conveying reward through cues, hence producing rapid and early perceptual associations, leading to an asymptotic learning curve early on in the task. This would still be consistent with the conclusion that no learning occurred. In other words, if participants mapped the reward values rapidly enough to produce sustained changes from the early half to the late half of the task, that means no new information needed to be learned, hence the temporal-difference prediction error term remained constant over time (Berridge, 2007; Schultz, 2002). Any prediction error change would need to have happened during the first few trials of the task, and then plateau from that point on. Many of the value-driven effects found in related studies have found positive results in early perceptual measures such as RT or early ERP indices (Chelazzi et al., 2014; Hickey et al., 2010; Munneke et al., 2016), or in tasks where early selection is emphasized (Failing & Theeuwes, 2014; MacLean & Giesbrecht, 2015b), suggesting that mapping reward to any stimulus feature is necessarily rapid and occurs early in the task. Reinforcement-learning work suggests this might be the case during gambling-like tasks

(Krigolson, Hassall, & Handy, 2014). The conclusion from the current null findings in both studies is consistent with this possibility.

It is also possible that the measures did not capture the transient changes in the neural signal during the acquisition of reward values: the temporal factor in both studies was operationalized as a median split of the trial order for each participant, potentially washing out reward-driven modulations if any. Future work should use alternative ways to measure these learning signals in behavior and in the neural indices, such as using bins of trials (Failing & Theeuwes, 2014; Raymond & O'Brien, 2009) to provide more moments in measuring long-term changes induced by learning. The current measures also used single-trial mean amplitudes to capture ERPs across time; this presents a potential issue as the trialwise signal is noisy and subject to latency jitter. Employing an ERP Principal Components Analysis (ERP-PCA) would be more sensitive to the variance of the potential signal driven by the reward condition, compared to single-trial mean amplitude measures (Dien, 2010).

Future work examining the influence of reward-learning should measure overt behavior (accuracy, RT) whenever any reward values are being acquired. This was a limitation in Study 2, in which no keypresses to the rewarded feature were measured, thus any changes in overt learning behavior could not be captured. For this reason, two-phase designs with separate learning and perceptual tasks as described previously would address this issue. The value-acquisition phase makes use of trialwise choice decisions to assess learning behavior, and hence can capture overt motor actions to reward outcomes at each moment (Raymond & O'Brien, 2009). This would also allow any rapid learning signals occurring in the first few trials to be measured.

Conclusion

The current study suggests that reward can exert robust effects on mechanisms of exogenous and endogenous attention when it is attached to low-level stimulus properties. While no effects of reward were found when motivational information was conveyed by higher-level stimulus properties such as target information, the potential of reward to exert measurable impact on higher-level processes such as object categorization cannot yet be ruled out. Stimuli associated with reward facilitate detection when they are subsequent task targets but no longer rewarded, or interfere with target detection when they are distractors (Anderson, Laurent, & Yantis, 2011a; Failing & Theeuwes, 2014; Munneke et al., 2016). It is entirely possible that reward's biasing of sensory processing of low-level stimulus features can fully explain these findings. However, is also possible that generalizing this bias to higher-level features such as target shape might account for the lingering (and robust) effects of reward capture days, even months, after the reward information was initially associated with the stimuli (Anderson & Yantis, 2013; MacLean & Giesbrecht, 2015b). If reward attachment is not stimulus-specific but feature-based, the lingering question is whether there is a time during the consolidation of reward-based learning that it does become stimulus-specific. Rossi et al. (2017) have investigated this and found gain-driven effects in stimuli on the P300 ERP that did not generalize to new contexts, ruling out a feature-based explanation for reward, but more work, especially in the mapping of reward during later stages of processing, is necessary.

Table 1. Value x Cue Repeated-Measures ANOVA Results for Mean RTs (Reaction Times) to Targets (Study 1)

Source	*SS*	*df*	*Mean Square*	*F*	*p*	η_p^2
Value	36378.565	2	18189.282	30.716	.000	.467
Error(Value)	41452.791	70	592.183			
Cue	86409.448	2	43204.724	124.941	.000	.781
Error(Cue)	24206.092	70	345.801			
Value * Cue	3218.751	4	804.688	5.612	.000	.138
Error(Value*Cue)	20075.488	140	143.396			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 2. Paired *t*-test Results for Mean RTs to Targets (Study 1)

Pair	*Mean difference*	*SD*	*SEM*	*t(35)*	*p*
Reward_Valid - Reward_Invalid	-19.3903395	20.5417359	3.4236226	-5.664	.000
Reward_Valid - Reward_Uncued	-46.5629693	19.3462021	3.2243670	-14.441	.000
Reward_Valid - Nonreward_Valid	-34.9551267	27.2822328	4.5470388	-7.687	.000
Reward_Valid - Nonreward_Invalid	-39.5439549	38.6631923	6.4438654	-6.137	.000
Reward_Valid - Nonreward_Uncued	-64.6794198	26.6610867	4.4435144	-14.556	.000
Reward_Valid - Neutral_Valid	-9.5292172	25.3555730	4.2259288	-2.255	.030
Reward_Valid - Neutral_Invalid	-20.0672477	25.5114437	4.2519073	-4.720	.000
Reward_Valid - Neutral_Uncued	-50.0374982	22.4364419	3.7394070	-13.381	.000

Note. *SD* = standard deviation; *SEM* = standard error of the mean.

Table 3. Time x Block x Cue Repeated-Measures ANOVA for Mean RTs to Targets (Study 1)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Time	45739.217	1	45739.217	40.656	.000	.537
Error(Time)	39376.380	35	1125.039			
Block	6078.072	1	6078.072	8.790	.005	.201
Error(Block)	24202.966	35	691.513			
Cue	118127.332	2	59063.666	135.330	.000	.795
Error(Cue)	30550.851	70	436.441			
Time * Block	50.522	1	50.522	.114	.737	.003
Error(Time*Block)	15474.335	35	442.124			
Time * Cue	1381.747	2	690.874	5.088	.009	.127
Error(Time*Cue)	9504.678	70	135.781			
Block * Cue	256.669	2	128.334	.677	.512	.019
Error(Block*Cue)	13278.580	70	189.694			
Time * Block * Cue	160.261	2	80.130	.411	.664	.012
Error(Time*Block*Cue)	13638.245	70	194.832			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 4. Bin x Block x Cue Repeated-Measures ANOVA for Mean RTs to Targets (Study 1)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Bin	164599.113	3	54866.371	33.755	.000	.491
Error(Bin)	170669.452	105	1625.423			
Block	11532.694	1	11532.694	8.032	.008	.187
Error(Block)	50255.806	35	1435.880			
Cue	236773.582	2	118386.791	135.429	.000	.795
Error(Cue)	61191.107	70	874.159			
Bin * Block	1381.239	3	460.413	.391	.760	.011
Error(Bin*Block)	123582.268	105	1176.974			
Bin * Cue	5910.464	6	985.077	3.671	.002	.095
Error(Bin*Cue)	56352.355	210	268.345			
Block * Cue	423.152	2	211.576	.534	.589	.015
Error(Block*Cue)	27739.954	70	396.285			
Bin * Block * Cue	542.003	6	90.334	.243	.962	.007
Error(Bin*Block*Cue)	78121.378	210	372.007			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 5. Time x Block x Cue x Box Color Repeated-Measures ANOVA for Mean RTs to Targets (Study 1)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Time	91478.434	1	91478.434	40.656	.000	.537
Error(Time)	78752.761	35	2250.079			
Block	12156.144	1	12156.144	8.790	.005	.201
Error(Block)	48405.932	35	1383.027			
Cue	236254.664	2	118127.332	135.330	.000	.795
Error(Cue)	61101.702	70	872.881			
Box Color	54111.705	1	54111.705	33.605	.000	.490
Error(Box Color)	56357.461	35	1610.213			
Time * Block	101.045	1	101.045	.114	.737	.003
Error(Time*Block)	30948.671	35	884.248			
Time * Cue	2763.495	2	1381.747	5.088	.009	.127
Error(Time*Cue)	19009.355	70	271.562			
Block * Cue	513.337	2	256.669	.677	.512	.019
Error(Block*Cue)	26557.161	70	379.388			
Time * Block * Cue	320.522	2	160.261	.411	.664	.012
Error(Time*Block*Cue)	27276.490	70	389.664			
Time * Box Color	4004.527	1	4004.527	9.881	.003	.220
Error(Time*Box Color)	14184.558	35	405.273			
Block * Box Color	16025.669	1	16025.669	27.398	.000	.439
Error(Block*Box Color)	20472.609	35	584.932			
Time * Block * Box Color	393.616	1	393.616	1.066	.309	.030
Error(Time*Block*Box Color)	12929.419	35	369.412			
Cue * Box Color	4889.806	2	2444.903	7.476	.001	.176
Error(Cue*Box Color)	22892.102	70	327.030			
Time * Cue * Box Color	446.458	2	223.229	.627	.537	.018
Error(Time*Cue*Box Color)	24939.147	70	356.274			
Block * Cue * Box Color	1793.641	2	896.820	2.674	.076	.071
Error(Block*Cue*Box Color)	23479.698	70	335.424			
Time * Block * Cue * Box Color	563.032	2	281.516	.837	.437	.023
Error(Time*Block*Cue*Box Color)	23540.273	70	336.290			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 6. Value x Stimulus x Cue Repeated-Measures ANOVA for Mean P1 Amplitudes (Study 1)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Value	.748	2	.374	.619	.542	.017
Error(Value)	42.290	70	.604			
Stimulus	.075	1	.075	.149	.702	.004
Error(Stimulus)	17.644	35	.504			
Cue	18.071	2	9.035	4.705	.012	.119
Error(Cue)	134.424	70	1.920			
Value * Stimulus	1.129	2	.565	1.163	.318	.032
Error(Value*Stimulus)	33.966	70	.485			
Value * Cue	3.352	4	.838	1.452	.220	.040
Error(Value*Cue)	80.797	140	.577			
Stimulus * Cue	.480	2	.240	.466	.629	.013
Error(Stimulus*Cue)	36.034	70	.515			
Value * Stimulus * Cue	.560	4	.140	.257	.905	.007
Error(Value*Stimulus*Cue)	76.181	140	.544			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 7. Value x Stimulus x Cue Repeated-Measures ANOVA for Mean N1 Amplitudes (Study 1)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Value	4.331	2	2.165	2.969	.058	.078
Error(Value)	51.058	70	.729			
Stimulus	35.550	1	35.550	30.282	.000	.464
Error(Stimulus)	41.089	35	1.174			
Cue	1.981	2	.990	.638	.531	.018
Error(Cue)	108.649	70	1.552			
Value * Stimulus	2.135	2	1.067	1.740	.183	.047
Error(Value*Stimulus)	42.931	70	.613			
Value * Cue	3.310	4	.828	1.022	.398	.028
Error(Value*Cue)	113.373	140	.810			
Stimulus * Cue	3.174	2	1.587	2.403	.098	.064
Error(Stimulus*Cue)	46.233	70	.660			
Value * Stimulus * Cue	2.875	4	.719	1.307	.270	.036
Error(Value*Stimulus*Cue)	76.973	140	.550			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 8. Value x Stimulus x Cue Repeated-Measures ANOVA for Mean P2a Amplitudes (Study 1)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Value	50.732	2	25.366	12.998	.000	.271
Error(Value)	136.607	70	1.952			
Stimulus	173.626	1	173.626	68.288	.000	.661
Error(Stimulus)	88.989	35	2.543			
Cue	26.238	2	13.119	3.933	.024	.101
Error(Cue)	233.473	70	3.335			
Value * Stimulus	5.474	2	2.737	2.279	.110	.061
Error(Value*Stimulus)	84.052	70	1.201			
Value * Cue	5.444	4	1.361	1.175	.324	.032
Error(Value*Cue)	162.124	140	1.158			
Stimulus * Cue	5.129	2	2.565	1.891	.159	.051
Error(Stimulus*Cue)	94.938	70	1.356			
Value * Stimulus * Cue	.192	4	.048	.039	.997	.001
Error(Value*Stimulus*Cue)	170.674	140	1.219			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 9. Time x Block Type x Cue Repeated-Measures ANOVA for Mean P1 Amplitudes (Study 1)

Source	SS	df	MS	F	p	η_p^2
Time	2.450	1	2.450	3.609	.066	.093
Error(Time)	23.758	35	.679			
Block Type	.020	1	.020	.042	.838	.001
Error(Block Type)	16.407	35	.469			
Cue	11.584	2	5.792	4.542	.014	.115
Error(Cue)	89.274	70	1.275			
Time * Block Type	.601	1	.601	1.703	.200	.046
Error(Time*Block Type)	12.355	35	.353			
Time * Cue	.332	2	.166	.451	.639	.013
Error(Time*Cue)	25.762	70	.368			
Block Type * Cue	.879	2	.439	1.432	.246	.039
Error(Block Type*Cue)	21.481	70	.307			
Time * Block Type * Cue	.386	2	.193	.655	.523	.018
Error(Time*Block Type*Cue)	20.625	70	.295			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 10. Time x Block Type x Cue Repeated-Measures ANOVA for Mean N1 Amplitudes (Study 1)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Time	2.600	1	2.600	2.089	.157	.056
Error(Time)	43.554	35	1.244			
Block Type	1.525	1	1.525	3.305	.078	.086
Error(Block Type)	16.147	35	.461			
Cue	1.263	2	.631	.612	.545	.017
Error(Cue)	72.277	70	1.033			
Time * Block Type	.258	1	.258	.361	.552	.010
Error(Time*Block Type)	25.037	35	.715			
Time * Cue	.012	2	.006	.015	.986	.000
Error(Time*Cue)	29.221	70	.417			
Block Type * Cue	.085	2	.043	.089	.915	.003
Error(Block Type*Cue)	33.613	70	.480			
Time * Block Type * Cue	.096	2	.048	.147	.864	.004
Error(Time*Block Type*Cue)	22.746	70	.325			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 11. Time x Block Type x Cue Repeated-Measures ANOVA for Mean P2a Amplitudes (Study 1)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Time	6.691	1	6.691	3.607	.066	.093
Error(Time)	64.918	35	1.855			
Block Type	38.406	1	38.406	25.837	.000	.425
Error(Block Type)	52.027	35	1.486			
Cue	15.986	2	7.993	3.995	.023	.102
Error(Cue)	140.065	70	2.001			
Time * Block Type	.005	1	.005	.004	.949	.000
Error(Time*Block Type)	41.315	35	1.180			
Time * Cue	1.407	2	.703	.882	.418	.025
Error(Time*Cue)	55.802	70	.797			
Block Type * Cue	1.940	2	.970	1.400	.253	.038
Error(Block Type*Cue)	48.497	70	.693			
Time * Block Type * Cue	7.082	2	3.541	4.644	.013	.117
Error(Time*Block Type*Cue)	53.371	70	.762			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 12. Time x Block Type x Stimulus Repeated-Measures ANOVA for Mean P1 Amplitudes (Study 1)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Time	1.056	1	1.056	3.013	.091	.079
Error(Time)	12.265	35	.350			
Block Type	.002	1	.002	.006	.940	.000
Error(Block Type)	13.224	35	.378			
Stimulus	.260	1	.260	1.118	.298	.031
Error(Stimulus)	8.124	35	.232			
Time * Block Type	.308	1	.308	1.020	.319	.028
Error(Time*Block Type)	10.571	35	.302			
Time * Stimulus	.041	1	.041	.124	.727	.004
Error(Time*Stimulus)	11.631	35	.332			
Block Type * Stimulus	2.039	1	2.039	7.928	.008	.185
Error(Block Type*Stimulus)	9.001	35	.257			
Time * Block Type * Stimulus	.005	1	.005	.021	.886	.001
Error(Time*Block Type*Stimulus)	8.296	35	.237			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 13. Time x Block Type x Stimulus Repeated-Measures ANOVA for Mean N1 Amplitudes (Study 1)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Time	.959	1	.959	1.300	.262	.036
Error(Time)	25.827	35	.738			
Block Type	.718	1	.718	1.786	.190	.049
Error(Block Type)	14.081	35	.402			
Stimulus	13.691	1	13.691	28.455	.000	.448
Error(Stimulus)	16.841	35	.481			
Time * Block Type	.141	1	.141	.259	.614	.007
Error(Time*Block Type)	19.032	35	.544			
Time * Stimulus	.304	1	.304	.776	.385	.022
Error(Time*Stimulus)	13.723	35	.392			
Block Type * Stimulus	1.591	1	1.591	5.612	.023	.138
Error(Block Type*Stimulus)	9.925	35	.284			
Time * Block Type * Stimulus	.398	1	.398	1.485	.231	.041
Error(Time*Block Type*Stimulus)	9.383	35	.268			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 14. Time x Block Type x Stimulus Repeated-Measures ANOVA for Mean P2a Amplitudes (Study 1)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Time	3.823	1	3.823	2.616	.115	.070
Error(Time)	51.160	35	1.462			
Block Type	28.155	1	28.155	29.319	.000	.456
Error(Block Type)	33.610	35	.960			
Stimulus	70.655	1	70.655	75.222	.000	.682
Error(Stimulus)	32.875	35	.939			
Time * Block Type	.015	1	.015	.017	.897	.000
Error(Time*Block Type)	31.832	35	.909			
Time * Stimulus	1.566	1	1.566	2.911	.097	.077
Error(Time*Stimulus)	18.825	35	.538			
Block Type * Stimulus	.124	1	.124	.220	.642	.006
Error(Block Type*Stimulus)	19.717	35	.563			
Time * Block Type * Stimulus	.104	1	.104	.226	.637	.006
Error(Time*Block Type*Stimulus)	16.065	35	.459			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 15. Task x Stimulus Repeated-Measures ANOVA for Mean P2a (Anterior) Amplitudes (Study 2)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Task	.343	1	.343	.196	.660	.003
Error(Task)	112.287	64	1.754			
Stimulus	150.271	1	150.271	49.973	.000	.438
Error(Stimulus)	192.452	64	3.007			
Task * Stimulus	4.257	1	4.257	3.828	.055	.056
Error(Task*Stimulus)	71.171	64	1.112			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 16. ROI x Task x Stimulus Repeated-Measures ANOVA for Mean N2b (Posterior) Amplitudes (Study 2)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
ROI	3.348	1	3.348	3.698	.059	.055
Error(ROI)	57.930	64	.905			
Task	2.073	1	2.073	3.539	.064	.052
Error(Task)	37.483	64	.586			
Stimulus	95.270	1	95.270	64.014	.000	.500
Error(Stimulus)	95.249	64	1.488			
ROI * Task	4.987	1	4.987	10.834	.002	.145
Error(ROI*Task)	29.458	64	.460			
ROI * Stimulus	.334	1	.334	.451	.504	.007
Error(ROI*Stimulus)	47.421	64	.741			
Task * Stimulus	.070	1	.070	.104	.748	.002
Error(Task*Stimulus)	42.942	64	.671			
ROI * Task * Stimulus	8.950	1	8.950	19.716	.000	.236
Error(ROI*Task*Stimulus)	29.053	64	.454			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 17. Task x Stimulus Repeated-Measures ANOVA for Mean P1 Amplitudes (Study 2)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Task	.915	1	.915	1.591	.212	.024
Error(Task)	36.794	64	.575			
Stimulus	1.634	1	1.634	3.830	.055	.056
Error(Stimulus)	27.311	64	.427			
Task * Stimulus	.023	1	.023	.062	.804	.001
Error(Task*Stimulus)	23.565	64	.368			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 18. Task x Stimulus Repeated-Measures ANOVA for Mean N1 Amplitudes (Study 2)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Task	8.228	1	8.228	11.729	.001	.155
Error(Task)	44.898	64	.702			
Stimulus	14.502	1	14.502	16.585	.000	.206
Error(Stimulus)	55.964	64	.874			
Task * Stimulus	14.950	1	14.950	26.528	.000	.293
Error(Task*Stimulus)	36.068	64	.564			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 19. Task x Stimulus Repeated-Measures ANOVA for Peak P2a (Anterior) Latencies (Study 2)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Task	32961.848	1	32961.848	32.306	.000	.335
Error(Task)	65298.752	64	1020.293			
Stimulus	7221.376	1	7221.376	8.435	.005	.116
Error(Stimulus)	54791.444	64	856.116			
Task * Stimulus	85140.522	1	85140.522	108.895	.000	.630
Error(Task*Stimulus)	50038.829	64	781.857			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 20. ROI x Task x Stimulus Repeated-Measures ANOVA for Peak N2b (Posterior) Latencies (Study 2)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
ROI	278.943	1	278.943	1.586	.213	.024
Error(ROI)	11259.135	64	175.924			
Task	1093.547	1	1093.547	3.028	.087	.045
Error(Task)	23114.003	64	361.156			
Stimulus	6932.263	1	6932.263	16.711	.000	.207
Error(Stimulus)	26548.983	64	414.828			
ROI * Task	12542.645	1	12542.645	38.185	.000	.374
Error(ROI*Task)	21022.026	64	328.469			
ROI * Stimulus	5039.791	1	5039.791	17.161	.000	.211
Error(ROI*Stimulus)	18795.095	64	293.673			
Task * Stimulus	24386.563	1	24386.563	31.659	.000	.331
Error(Task*Stimulus)	49297.694	64	770.276			
ROI * Task * Stimulus	9925.625	1	9925.625	36.156	.000	.361
Error(ROI*Task*Stimulus)	17569.259	64	274.520			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 21. Time x Task x Stimulus Repeated-Measures ANOVA for Mean P2a (Anterior) Amplitudes (Study 2)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Time	.718	1	.718	.293	.591	.006
Error(Time)	112.705	46	2.450			
Task	1.043	1	1.043	.414	.523	.009
Error(Task)	115.769	46	2.517			
Stimulus	296.977	1	296.977	64.621	.000	.584
Error(Stimulus)	211.402	46	4.596			
Time * Task	.026	1	.026	.008	.930	.000
Error(Time*Task)	151.006	46	3.283			
Time * Stimulus	.572	1	.572	.298	.588	.006
Error(Time*Stimulus)	88.434	46	1.922			
Task * Stimulus	3.547	1	3.547	1.922	.172	.040
Error(Task*Stimulus)	84.881	46	1.845			
Time * Task * Stimulus	2.136	1	2.136	2.187	.146	.045
Error(Time*Task*Stimulus)	44.932	46	.977			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

Table 22. Time x ROI x Task x Stimulus Repeated-Measures ANOVA for Mean N2b (Posterior) Amplitudes (Study 2)

Source	*SS*	*df*	*MS*	*F*	*p*	η_p^2
Time	.150	1	.150	.118	.732	.003
Error(Time)	58.137	46	1.264			
ROI	10.154	1	10.154	5.483	.024	.106
Error(ROI)	85.188	46	1.852			
Task	2.181	1	2.181	2.389	.129	.049
Error(Task)	41.998	46	.913			
Stimulus	146.011	1	146.011	46.452	.000	.502
Error(Stimulus)	144.589	46	3.143			
Time * ROI	5.244	1	5.244	2.113	.153	.044
Error(Time*ROI)	114.173	46	2.482			
Time * Task	.030	1	.030	.017	.898	.000
Error(Time*Task)	84.606	46	1.839			
ROI * Task	7.261	1	7.261	10.081	.003	.180
Error(ROI*Task)	33.133	46	.720			
Time * ROI * Task	.170	1	.170	.115	.736	.003
Error(Time*ROI*Task)	67.766	46	1.473			
Time * Stimulus	.531	1	.531	.841	.364	.018
Error(Time*Stimulus)	29.035	46	.631			
ROI * Stimulus	.135	1	.135	.082	.776	.002
Error(ROI*Stimulus)	75.985	46	1.652			
Time * ROI * Stimulus	.003	1	.003	.004	.950	.000
Error(Time*ROI*Stimulus)	35.954	46	.782			
Task * Stimulus	.004	1	.004	.003	.957	.000
Error(Task*Stimulus)	57.957	46	1.260			
Time * Task * Stimulus	.026	1	.026	.039	.844	.001
Error(Time*Task*Stimulus)	31.109	46	.676			
ROI * Task * Stimulus	15.584	1	15.584	19.947	.000	.302
Error(ROI*Task*Stimulus)	35.939	46	.781			
Time * ROI * Task * Stimulus	.064	1	.064	.093	.761	.002
Error(Time*ROI*Task*Stimulus)	31.497	46	.685			

Note. *SS* = sum of squares; *df* = degrees of freedom; *MS* = mean square; η_p^2 = partial eta squared.

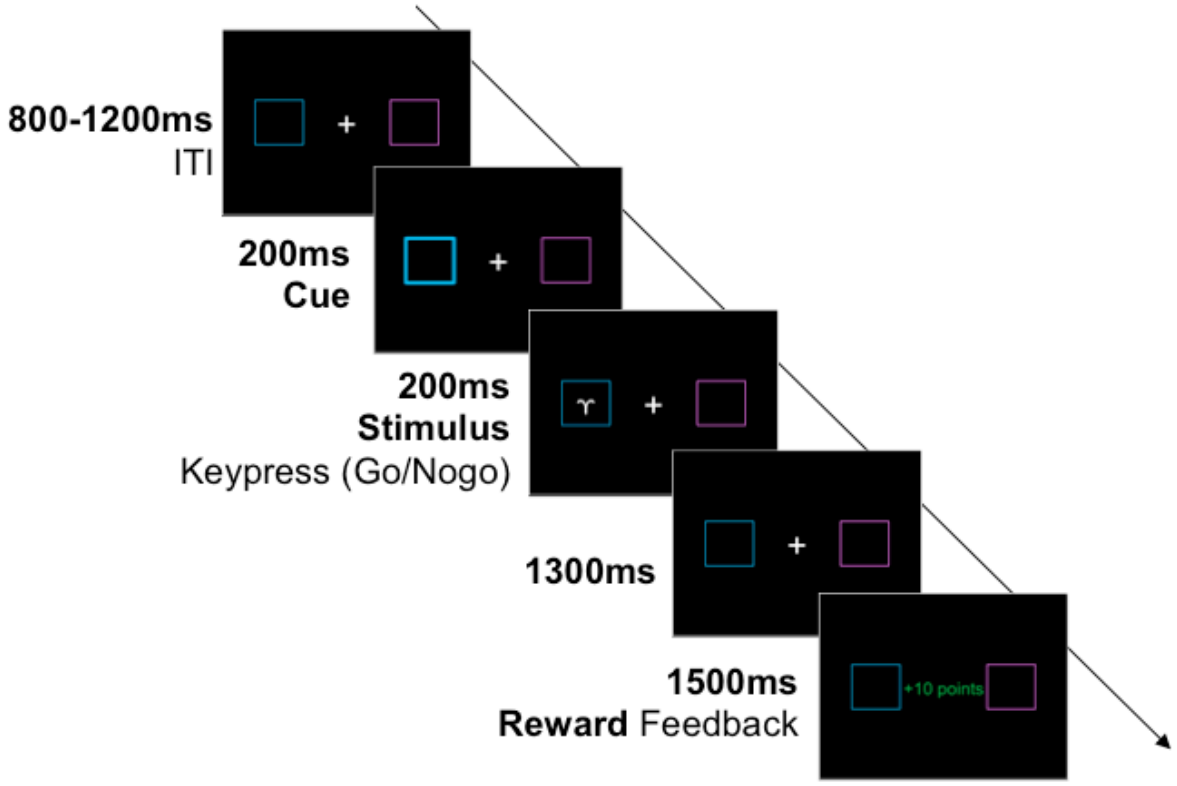

Figure 1. Trial Sequence for Spatial Cuing Task (Study 1).

An example of a trial in the spatial cuing task used in Study 1. The above trial demonstrates a Valid (Cue factor), Target (Stimulus factor), Reward (Value factor) condition.

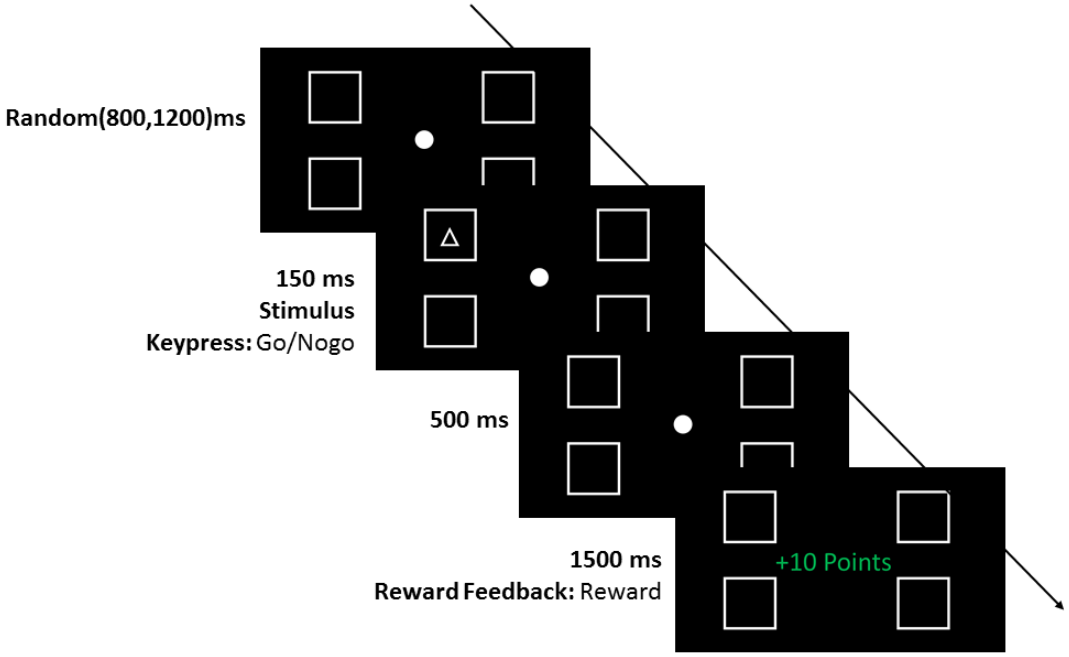

Figure 2. Trial Sequence for Target Detection Task (Study 2).

An example of a trial from the target detection task to be used in Study 2. The above illustrates an example of a rewarded nontarget (reward) trial.

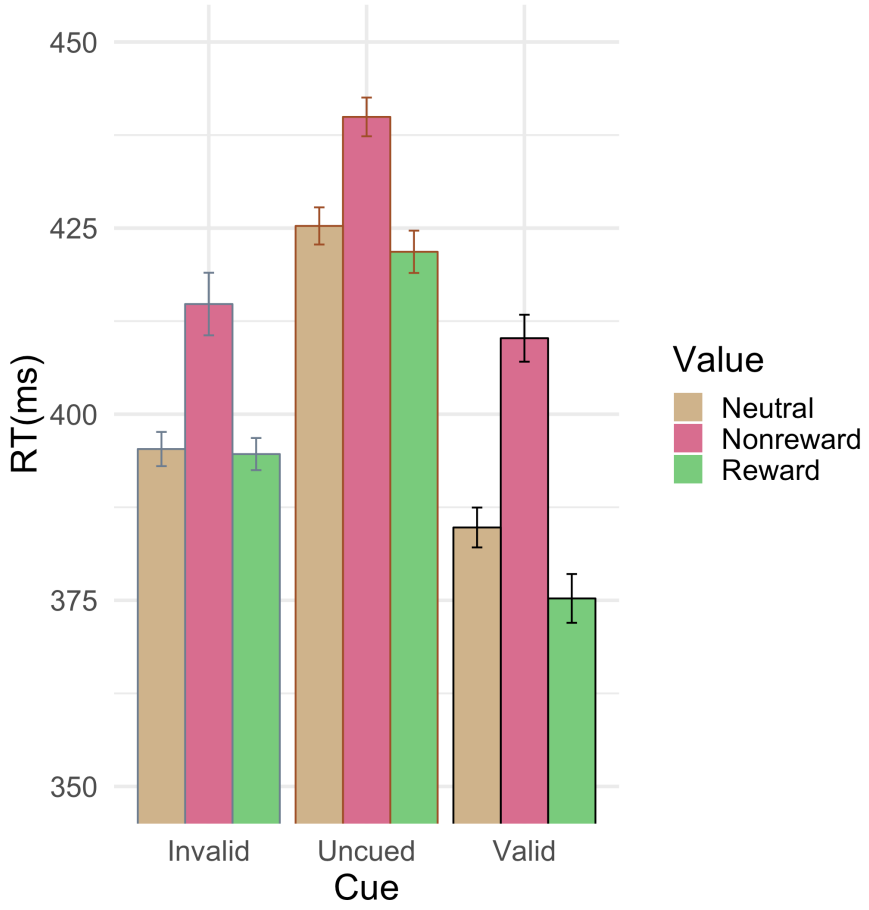

Figure 3. Mean RTs to Targets (Study 1).

Error bars represent standard error of the mean (SEM).

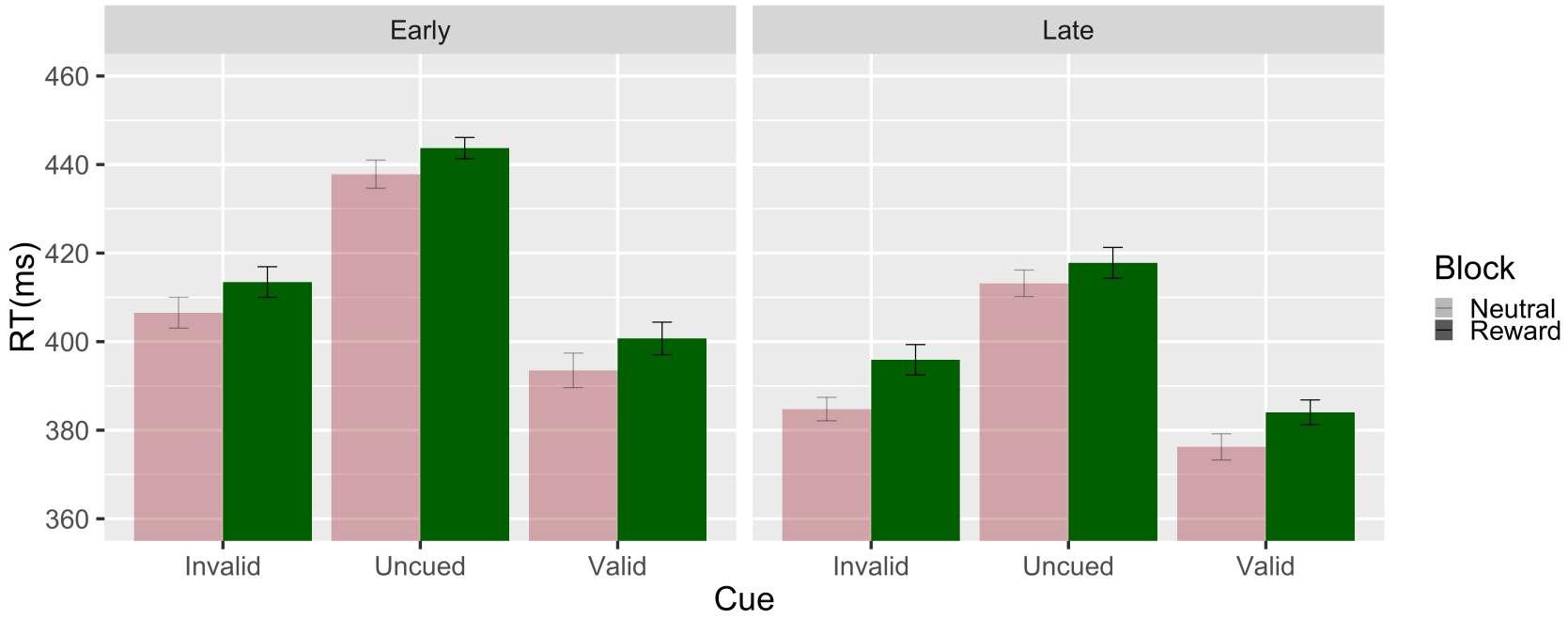

Figure 4. Mean RTs to Targets by Time (Early, Late), Block (Neutral, Reward), and Cue (Invalid, Uncued, Valid) (Study 1). Error bars represent SEM.

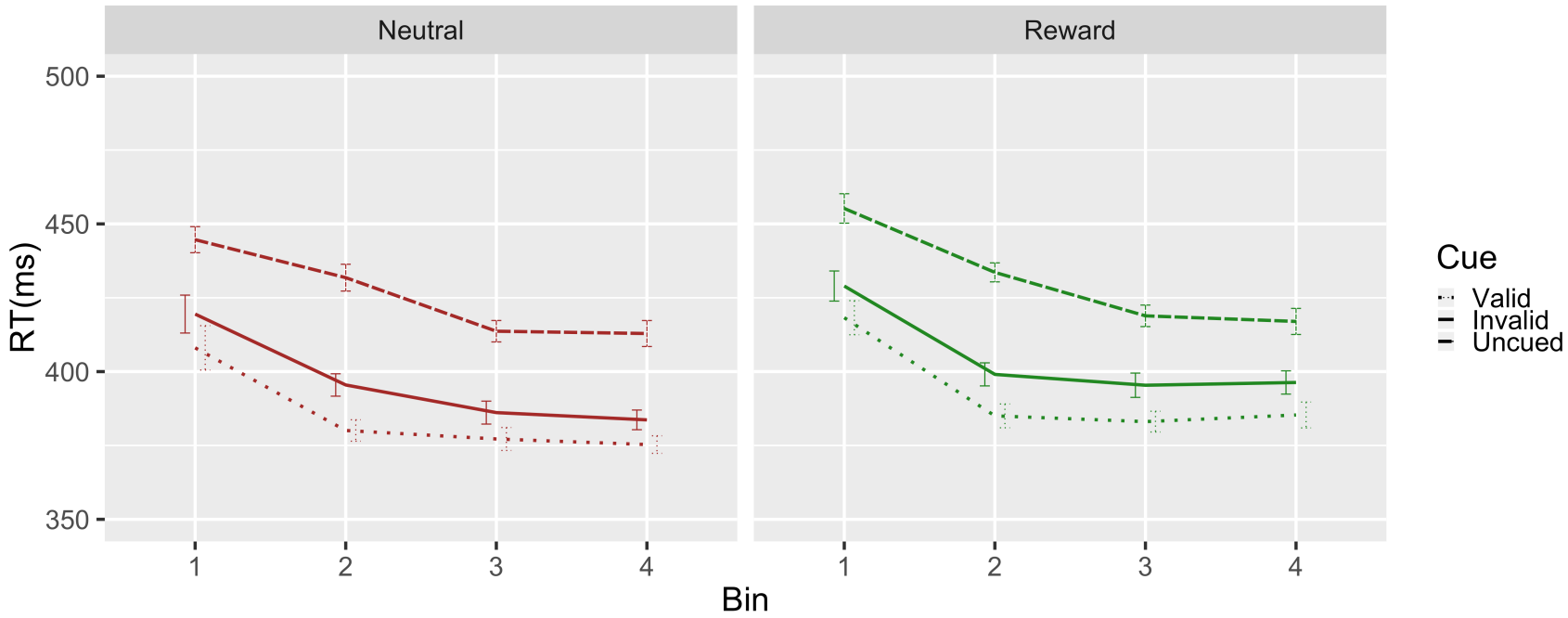

Figure 5. Mean RTs to Targets by Bin (1, 2, 3, 4), Block (Neutral, Reward), and Cue (Invalid, Uncued, Valid) (Study 1). Error bars represent SEM.

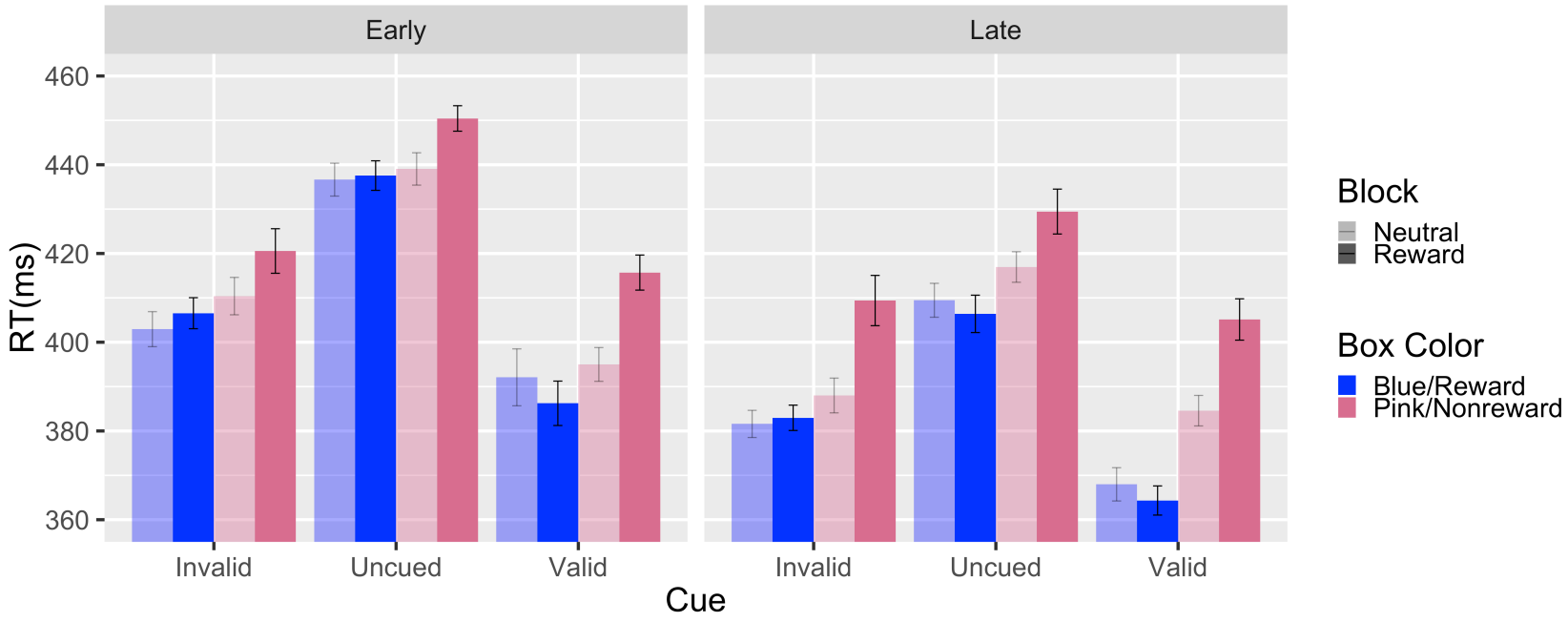

Figure 6. Mean RTs to Targets by Time, Block, and Box Color (Study 1).

Error bars represent SEM.

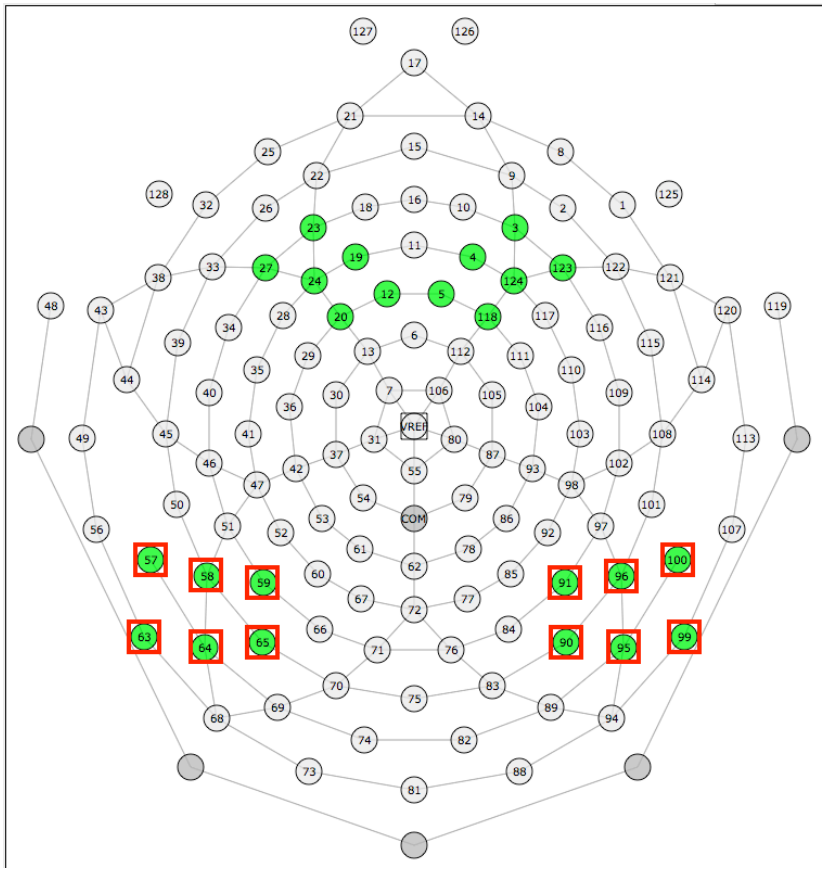

Figure 7. Electrode map for ERPs (Study 1).

Electrode map depicting mediofrontal ROIs (un-enclosed electrodes in front) for the P2a and lateral occipitotemporal ROI (enclosed in red squares) for the P1 and N1 ERPs.

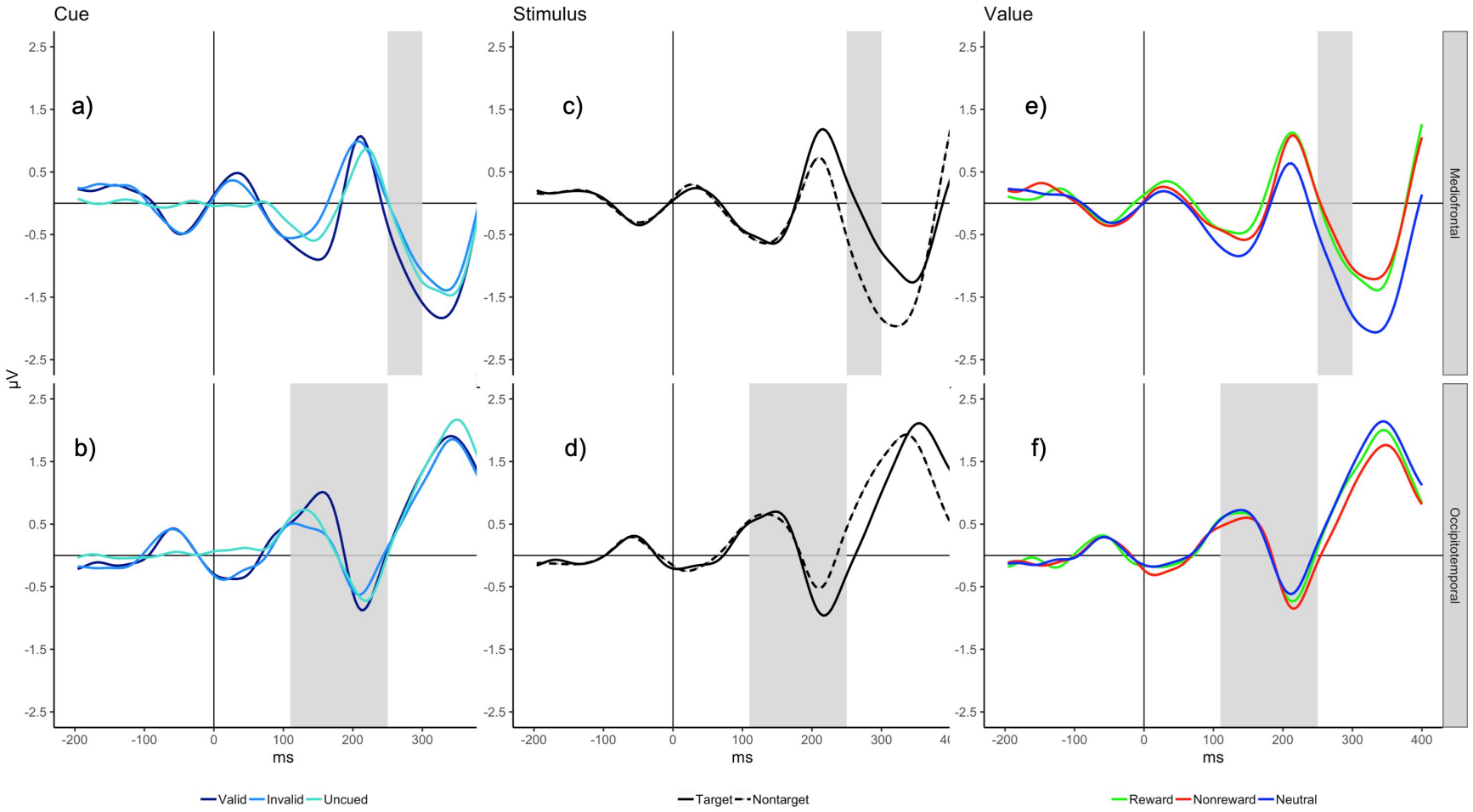

Figure 8. Grand-average ERPs by Main Effect and ROI (Study 1).

Shaded regions indicate time windows of analyses for P1 (110-180ms), N1 (190-250ms), and P2a (250-300ms) ERPs. Each vertical panel depicts averages of main effects of Cue, Stimulus, and Value, collapsing across all levels of all other factors.

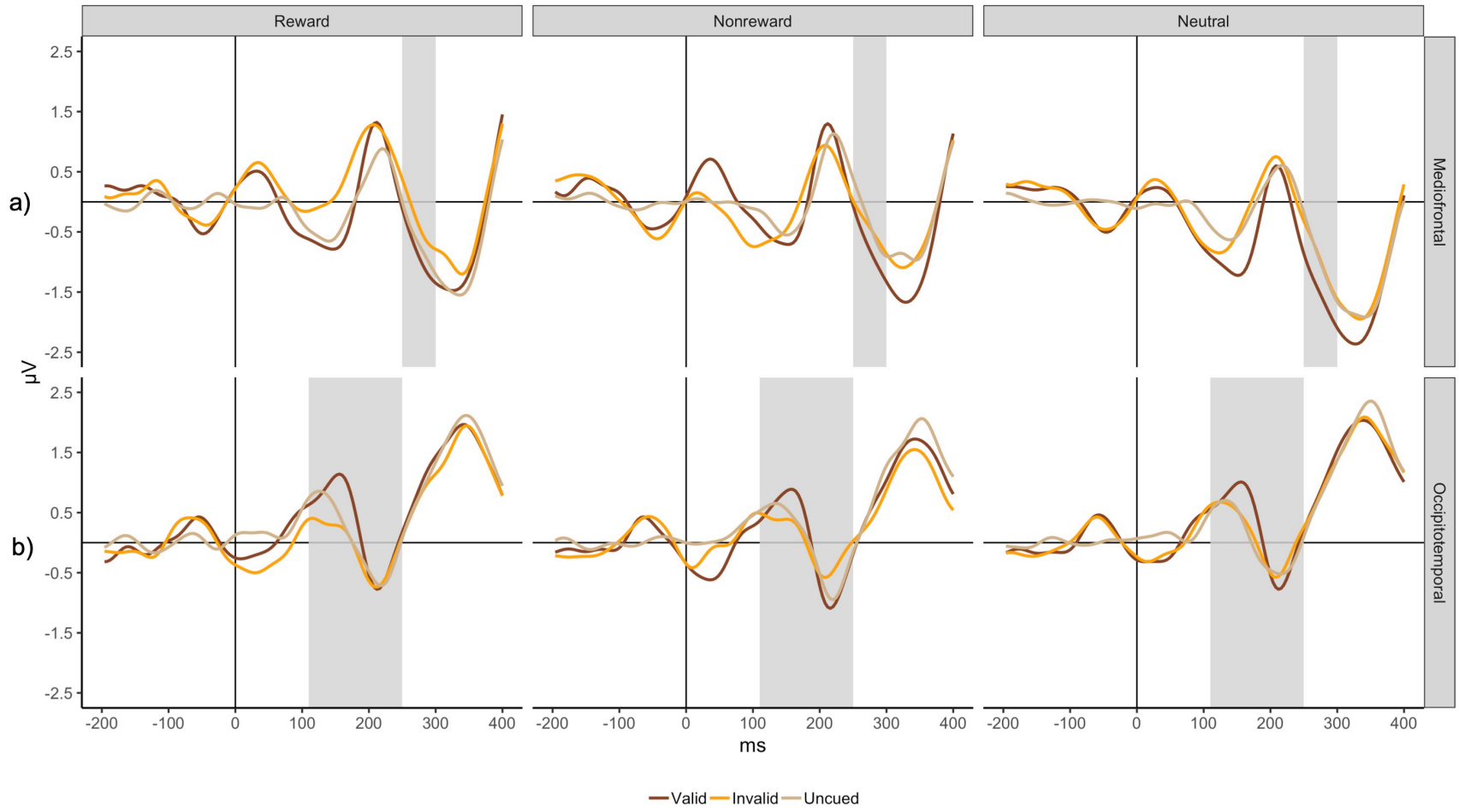

Figure 9. Grand-average ERPs by ROI, Value, and Cue (Study 1).

Each vertical panel represents Cue types (Valid, Invalid, Uncued) over mediofrontal and occipitotemporal sites at each level of the Value factor (Reward, Nonreward, Neutral).

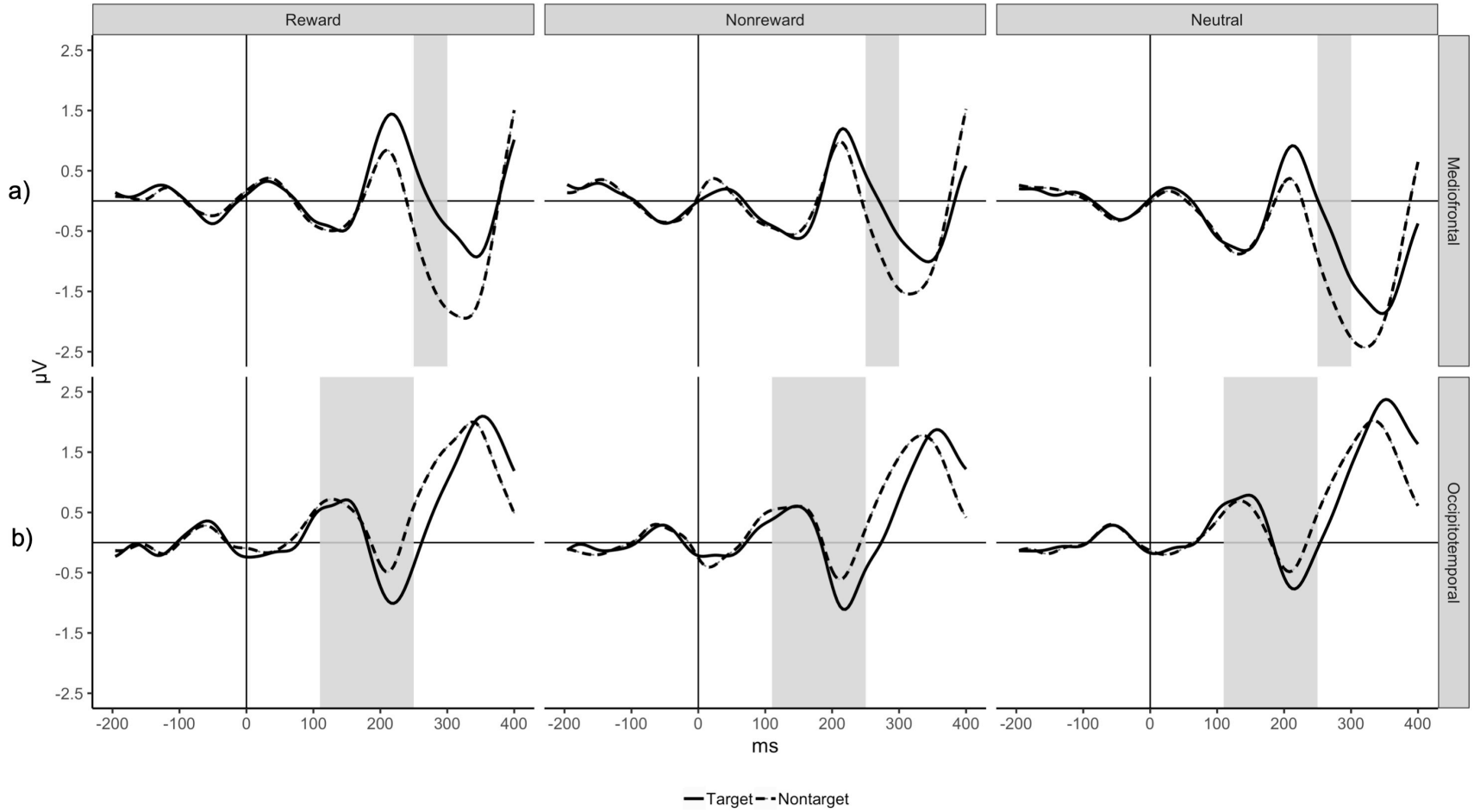

Figure 10. Grand-average ERPs by ROI, Value, and Stimulus (Study 1).

Each vertical panel represents Stimulus types (Target, Nontarget) over mediofrontal and occipitotemporal sites at each level of the Value factor (Reward, Nonreward, Neutral).

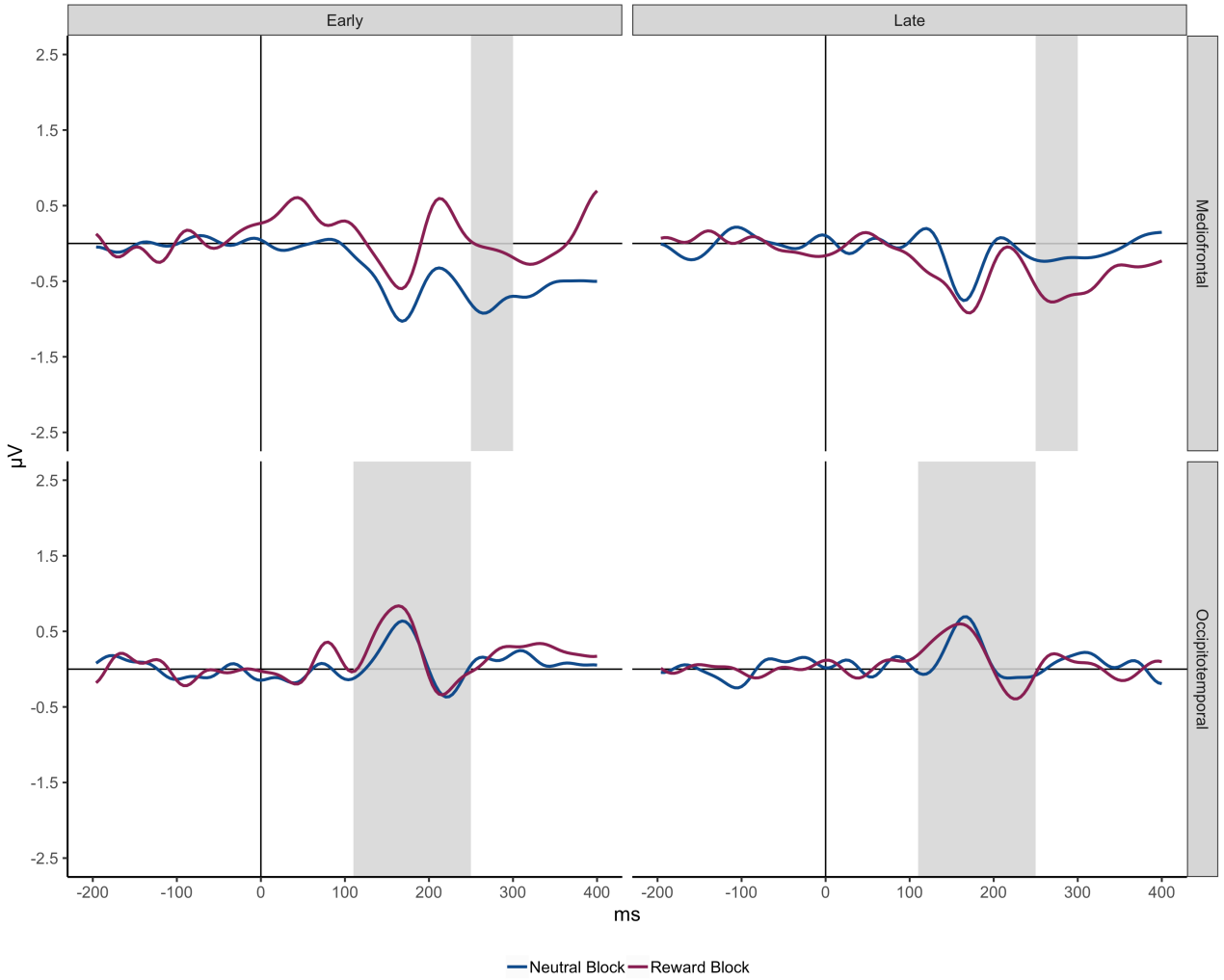

Figure 11. Cue Validity Difference-wave ERPs by Block, Time, and ROI (Study 1).

Each line represents a difference wave by subtracting Invalid from Valid waveforms.

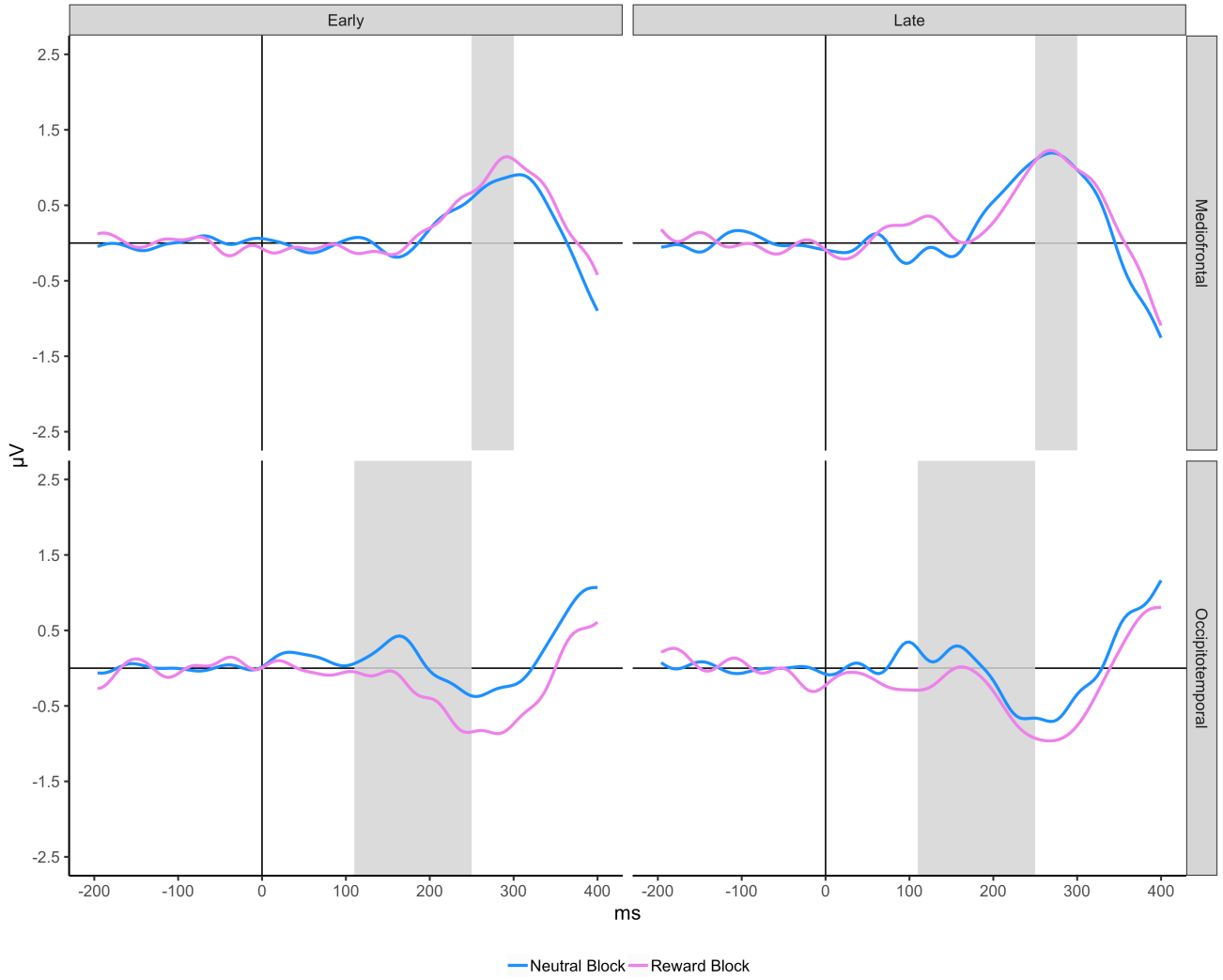

Figure 12. Target Difference-wave ERPs by Block, Time, and ROI (Study 1).

Each line represents a difference wave by subtracting Nontarget from Target waveforms.

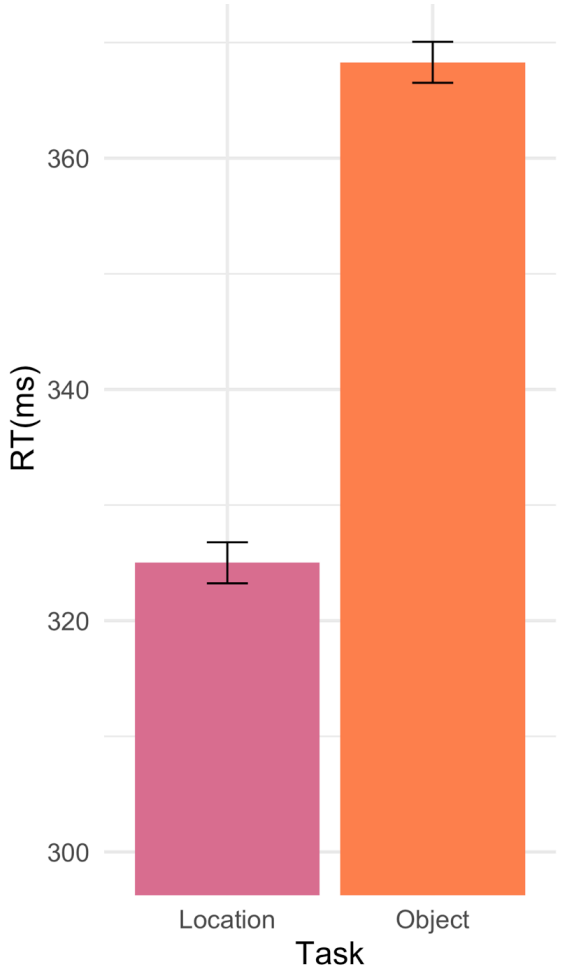

Figure 13. Mean RTs to Targets by Task (Study 2).

Error bars represent SEM.

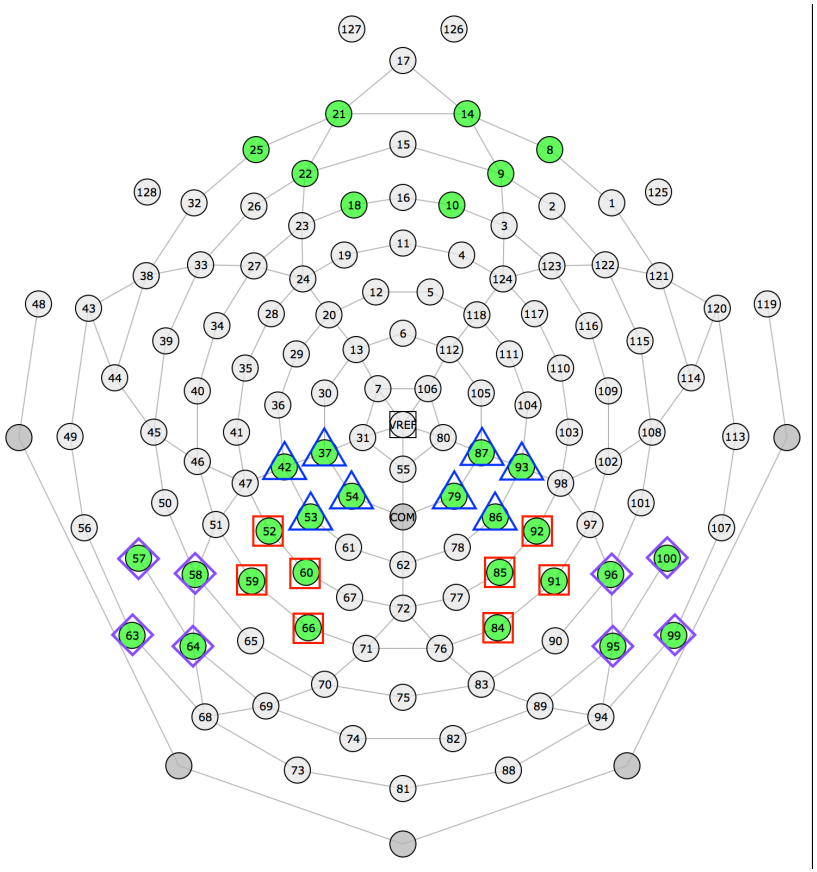

Figure 14. Electrode map for ERPs (Study 2).

Electrode map depicting mediofrontal ROIs (un-enclosed electrodes in front) for the P2a, lateral occipitotemporal ROI (red squares) for the P1 and N1, and dorsal (blue triangles) and ventral (violet diamonds) ROIs for the N2b.

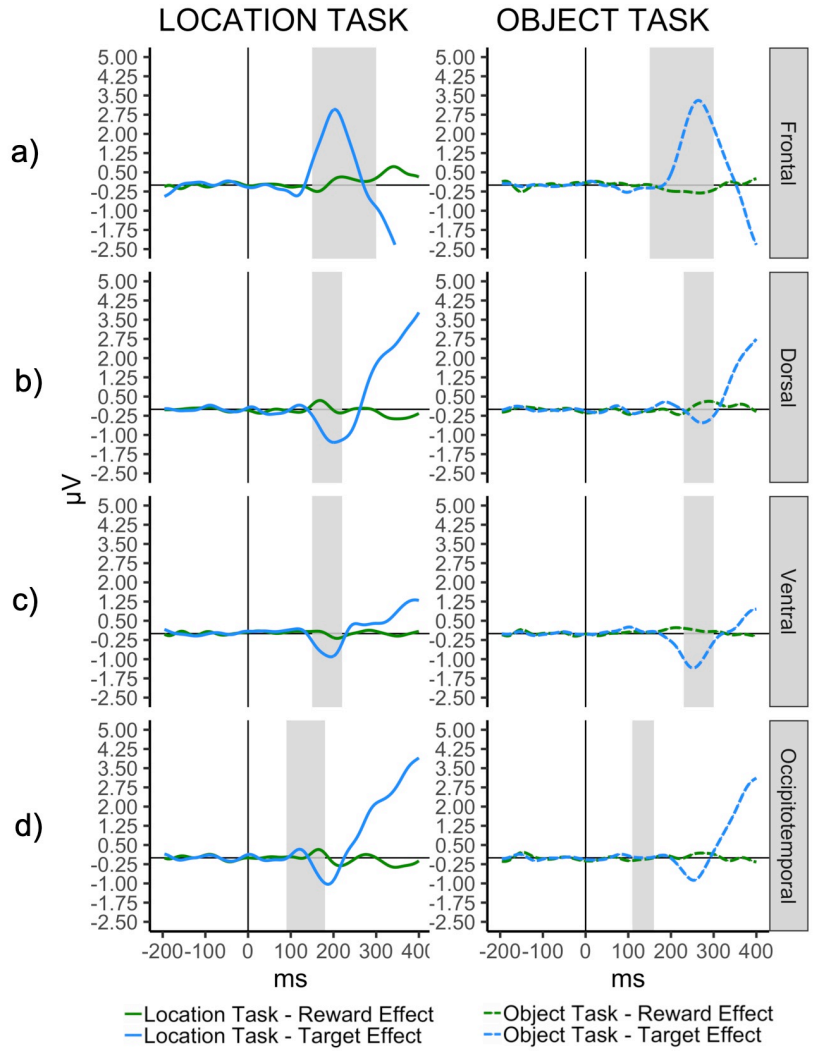

Figure 15. Difference-wave ERPs by Stimulus, Task, and ROI (Study 2).

Each line represents a difference wave by subtracting Nontarget from Target waveforms.

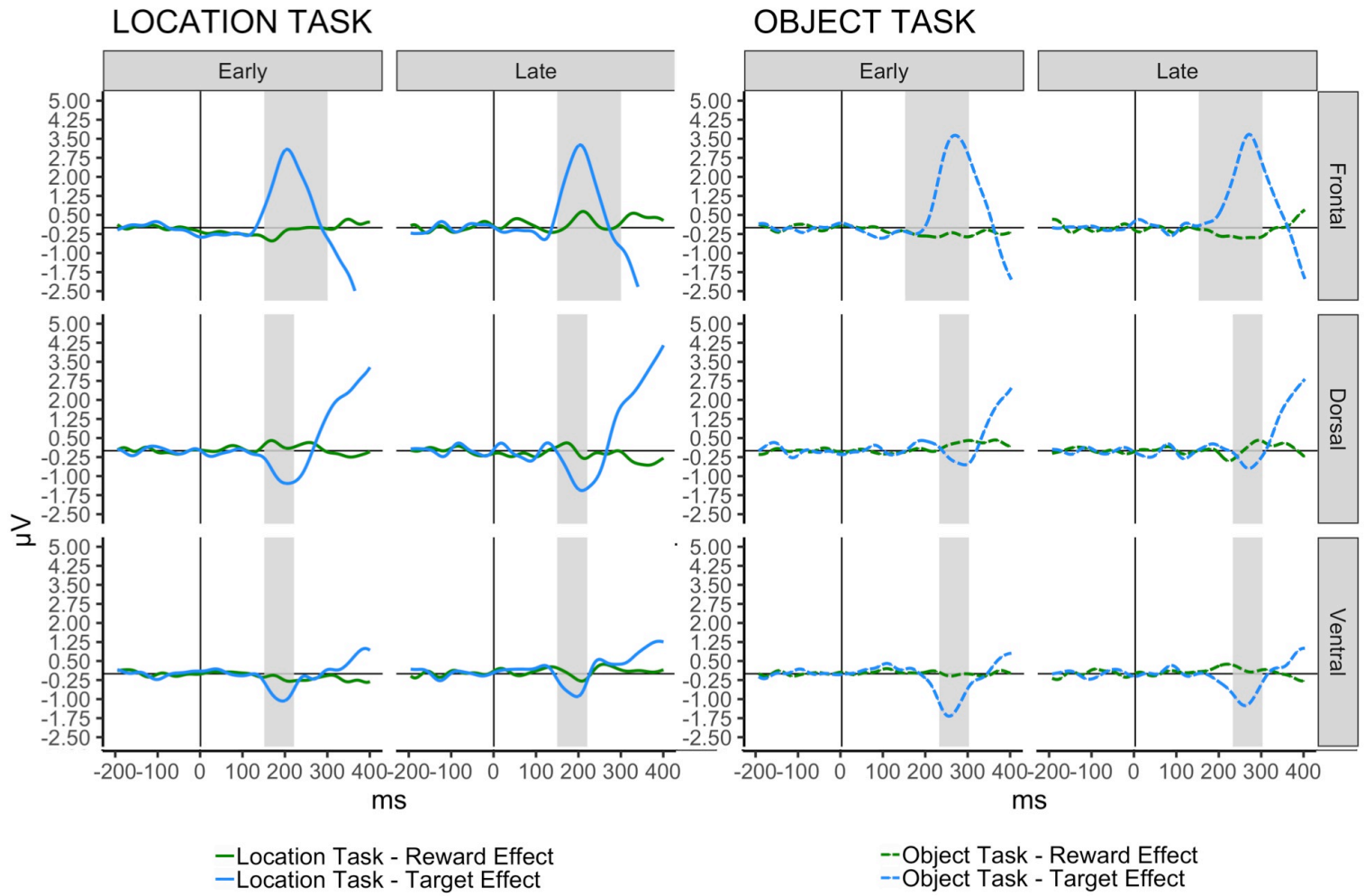

Figure 16. Difference-wave ERPs by Stimulus, Task, Time, and ROI (Study 2).

Each line represents a difference wave by subtracting Nontarget from Target waveforms. Analyses of Time were not performed on occipitotemporal waves (P1, N1 ERPs), hence they are not displayed.

References

Anderson, B. A., & Yantis, S. (2013). Persistence of value-driven attentional capture. *Journal of Experimental Psychology: Human Perception and Performance*, *39*(1), 6–9. http://doi.org/10.1037/a0030860

Anderson, B. A., Laurent, P. A., & Yantis, S. (2011a). Learned value magnifies salience-based attentional capture. *PLoS ONE*. http://doi.org/10.1371/journal.pone.0027926.g001

Anderson, B. A., Laurent, P. A., & Yantis, S. (2011b). Value-driven attentional capture. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(25), 10367–10371. http://doi.org/10.1073/pnas.1104047108

Berridge, K. C. (2007). The debate over dopamine's role in reward: The case for incentive salience. *Psychopharmacology*, *191*(3), 391–431. http://doi.org/10.1007/s00213-006-0578-x

Berridge, K. C., & Robinson, T. E. (1998). What is the role of dopamine in reward: Hedonic impact, reward learning, or incentive salience? *Brain Research. Brain Research Reviews*, *28*(3), 309–369.

Botvinick, M. M., Braver, T. S., Barch, D. M., Carter, C. S., & Cohen, J. D. (2001). Conflict monitoring and cognitive control. *Psychological Review*, *108*(3), 624–652. http://doi.org/10.1037//0033-295X.I08.3.624

Braver, T. S., & Cohen, I. D. (2000). On the control of control: The role of dopamine in regulating prefrontal function and working memory. In S. Monsell & J. Driver (Eds.), *Control of Cognitive Processes* (pp. 713–737). Cambridge.

Buschman, T. J., & Miller, E. K. (2007). Top-down versus bottom-up control of attention in the prefrontal and posterior parietal cortices. *Science*, *315*(5820), 1860–1862. http://doi.org/10.1126/science.1138071

Chelazzi, L., Eštočinová, J., Calletti, R., Gerfo, Lo, E., Sani, I., Libera, Della, C., & Santandrea, E. (2014). Altering spatial priority maps via reward-based learning. *Journal of Neuroscience*, *34*(25), 8594–8604. http://doi.org/10.1523/JNEUROSCI.0277-14.2014

Chelazzi, L., Miller, E. K., Duncan, J., & Desimone, R. (2001). Responses of neurons in macaque area V4 during memory-guided visual search. *Cerebral Cortex*, *11*(8), 761–772.

Corbetta, M., Miezin, F. M., Dobmeyer, S., Shulman, G. L., & Petersen, S. E. (1990). Attentional modulation of neural processing of shape, color, and velocity in humans. *Science*, *248*(4962), 1556–1559.

Corbetta, M., Miezin, F. M., Dobmeyer, S., Shulman, G. L., & Petersen, S. E. (1991). Selective and divided attention during visual discriminations of shape, color, and speed: Functional anatomy by positron emission tomography. *Journal of Neuroscience*, *11*(8), 2383–2402.

Desimone, R., & Duncan, J. (1995). Neural mechanisms of selective visual attention. *Annual Review of Neuroscience*, *18*, 193–222.

Dien, J. (2010). The ERP PCA Toolkit: An open source program for advanced statistical analysis of event-related potential data. *Journal of Neuroscience Methods*, *187*(1), 138–145. http://doi.org/10.1016/j.jneumeth.2009.12.009

Eriksen, C. W., & St James, J. D. (1986). Visual attention within and around the field of focal attention: A zoom lens model. *Perception & Psychophysics*, *40*(4), 225–240.

Failing, M. F., & Theeuwes, J. (2014). Exogenous visual orienting by reward. *Journal of Vision*, *14*(5), 1–9. http://doi.org/10.1167/14.5.6

Hickey, C., Chelazzi, L., & Theeuwes, J. (2010). Reward changes salience in human vision via the anterior cingulate. *Journal of Neuroscience*, *30*(33), 11096–11103. http://doi.org/10.1523/JNEUROSCI.1026-10.2010

Hillyard, S. A., & Anllo-Vento, L. (1998). Event-related brain potentials in the study of visual selective attention (Vol. 95, pp. 781–787). Presented at the Proceedings of the National Academy of Sciences.

Hillyard, S. A., Vogel, E. K., & Luck, S. J. (1998). Sensory gain control (amplification) as a mechanism of selective attention: electrophysiological and neuroimaging evidence. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *353*(1373), 1257–1270. http://doi.org/10.1098/rstb.1998.0281

Johnston, W. A., & Dark, V. J. (1986). Selective attention. *Annual Review of Psychology*, *37*, 43–75.

Katsuki, F., & Constantinidis, C. (2014). Bottom-up and top-down attention: Different processes and overlapping neural systems. *The Neuroscientist*, *20*(5), 509–521. http://doi.org/10.1177/1073858413514136

Krigolson, O. E., Hassall, C. D., & Handy, T. C. (2014). How We Learn to Make Decisions: Rapid Propagation of Reinforcement Learning Prediction Errors in Humans. *Journal of Cognitive Neuroscience*, *26*(3), 635–644. http://doi.org/10.1162/jocn_a_00509

Luck, S. J., Girelli, M., McDermott, M. T., & Ford, M. A. (1997). Bridging the gap between monkey neurophysiology and human perception: an ambiguity resolution theory of visual selective attention. *Cognitive Psychology*, *33*(1), 64–87. http://doi.org/10.1006/cogp.1997.0660

Luck, S. J., Heinze, H. J., Mangun, G. R., & Hillyard, S. A. (1990). Visual event-related potentials index focused attention within bilateral stimulus arrays. II. Functional dissociation of P1 and N1 components. *Electroencephalography and Clinical Neurophysiology*, *75*(6), 528–542.

Luque, D., Beesley, T., Morris, R. W., Jack, B. N., Griffiths, O., Whitford, T. J., & Le Pelley, M. E. (2017). Goal-directed and habit-like modulations of stimulus processing during reinforcement learning. *Journal of Neuroscience*, *37*(11), 3009–3017. http://doi.org/10.1523/JNEUROSCI.3205-16.2017

MacLean, M. H., & Giesbrecht, B. (2015a). Neural evidence reveals the rapid effects of reward history on selective attention. *Brain Research*, *1606*(C), 86–94. http://doi.org/10.1016/j.brainres.2015.02.016

MacLean, M. H., & Giesbrecht, B. (2015b). Neural evidence reveals the rapid effects of reward history on selective attention. *Brain Research*, *1606*(C), 86–94. http://doi.org/10.1016/j.brainres.2015.02.016

Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. *Annual Review of Neuroscience*, *24*, 167–202.

Munneke, J., Belopolsky, A. V., & Theeuwes, J. (2016). Distractors associated with reward break through the focus of attention. *Attention, Perception & Psychophysics*, *78*, 2213–2225. http://doi.org/10.3758/s13414-016-1075-x

Näätänen, R. (1992). Attention and automaticity in information processing. In *Attention and Brain Function* (pp. 11–71). Psychology Press.

Posner, M. I. (2014). Orienting of attention: Then and now. *The Quarterly Journal of Experimental Psychology*, *69*(10), 1864–1875. http://doi.org/10.1080/17470218.2014.937446

Posner, M. I., & Cohen, Y. (1984). Components of visual orienting. *Attention and Performance X: Control of Language Processes*, *32*, 531–556.

Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. *Annual Review of Neuroscience*, *13*(1), 25–42. http://doi.org/10.1146/annurev.ne.13.030190.000325

Posner, M. I., Snyder, C. R., & Davidson, B. J. (1980). Attention and the detection of signals. *Journal of Experimental Psychology: General*, *109*(2), 160–174.

Potts, G. F., & Tucker, D. M. (2001). Frontal evaluation and posterior representation in target detection. *Brain Research. Cognitive Brain Research*, *11*(1), 147–156. http://doi.org/10.1016/S0926-6410(00)00075-6

Potts, G. F., Martin, L. E., Burton, P., & Montague, P. R. (2006). When things are better or worse than expected: The medial frontal cortex and the allocation of processing resources. *Journal of Cognitive Neuroscience*, *18*(7), 1112–1119. http://doi.org/10.1162/jocn.2006.18.7.1112

Potts, G. F., Patel, S. H., & Azzam, P. N. (2004). Impact of instructed relevance on the visual ERP. *International Journal of Psychophysiology*, *52*(2), 197–209. http://doi.org/10.1016/j.ijpsycho.2003.10.005

Proudfit, G. H. (2015). The reward positivity: From basic research on reward to a biomarker for depression. *Psychophysiology*, *52*(4), 449–459. http://doi.org/10.1111/psyp.12370

Raymond, J. E., & O'Brien, J. L. (2009). Selective visual attention and motivation: The consequences of value learning in an attentional blink task. *Psychological Science*, *20*(8), 981–988. http://doi.org/10.1111/j.1467-9280.2009.02391.x

Rossi, V., Vanlessen, N., Bayer, M., Grass, A., Pourtois, G., & Schacht, A. (2017). Motivational salience modulates early visual cortex responses across task sets. *Journal of Cognitive Neuroscience*, *29*(6), 968–979. http://doi.org/10.1162/jocn_a_01093

Schultz, W. (2002). Getting formal with dopamine and reward. *Neuron*, *36*, 241–263.

Theeuwes, J. (1994). Endogenous and exogenous control of visual selection. *Perception*, *23*, 429–440.

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, *12*(1), 97–136. http://doi.org/10.1016/0010-0285(80)90005-5

Woodman, G. F. (2010). A brief introduction to the use of event-related potentials in studies of perception and attention. *Attention, Perception & Psychophysics*, *72*(8), 2031–2046. http://doi.org/10.3758/APP.72.8.2031

Appendix A: IRB Approval Letter

USF
UNIVERSITY OF
SOUTH FLORIDA

RESEARCH INTEGRITY AND COMPLIANCE
Institutional Review Boards, FWA No. 00001669
12901 Bruce B. Downs Blvd., MDC035 • Tampa, FL 33612-4799
(813) 974-5638 • FAX (813) 974-7091

June 23, 2017

Constanza de Dios
Psychology
4202 E Fowler Ave
PCD 4118G
Tampa, FL 33620-7200

RE: **Expedited Approval for Initial Review**
IRB#: Pro00030309
Title: Neural Responses to Exogenous Cues, Endogenous Targets, and Reward Outcomes

Study Approval Period: 6/23/2017 to 6/23/2018

Dear C. de Dios:

On 6/23/2017, the Institutional Review Board (IRB) reviewed and **APPROVED** the above application and all documents contained within, including those outlined below.

Approved Item(s):
Protocol Document(s):
RC Protocol IRB Pro00030309 Version 1.docx

Consent/Assent Document(s)*:
RC Consent Version 1.docx.pdf

*Please use only the official IRB stamped informed consent/assent document(s) found under the "Attachments" tab. Please note, these consent/assent documents are valid until the consent document is amended and approved.

It was the determination of the IRB that your study qualified for expedited review which includes activities that (1) present no more than minimal risk to human subjects, and (2) involve only procedures listed in one or more of the categories outlined below. The IRB may review research through the expedited review procedure authorized by 45CFR46.110. The research

proposed in this study is categorized under the following expedited review category:

(4) Collection of data through noninvasive procedures (not involving general anesthesia or sedation) routinely employed in clinical practice, excluding procedures involving x-rays or microwaves. Where medical devices are employed, they must be cleared/approved for marketing.

(7) Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies.

As the principal investigator of this study, it is your responsibility to conduct this study in accordance with IRB policies and procedures and as approved by the IRB. Any changes to the approved research must be submitted to the IRB for review and approval via an amendment. Additionally, all unanticipated problems must be reported to the USF IRB within five (5) calendar days.

We appreciate your dedication to the ethical conduct of human subject research at the University of South Florida and your continued commitment to human research protections. If you have any questions regarding this matter, please call 813-974-5638.

Sincerely,

John A Schinka, Ph.D.

John Schinka, Ph.D., Chairperson
USF Institutional Review Board