The Effect of Value Learning on Attentional Resources

During Top-Down Processing: An ERP Study

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Table of Contents

Table of Contents (Continued)

List of Tables

List of Figures

Abstract

Value learning has been shown to modulate attention. The current study investigated which elements of value learning (Probability or valence) influence attention. The P3 ERP component was examined as an index of attentional resources allocated to these valued stimuli and also as an index of the speed of processing these stimuli. Novel images were given a positive or negative (valence) value with variable probabilities of outcome (probability) in a learning task. Once the associations between stimuli and their expected values were made, the same stimuli were incorporated into a perceptual discrimination task where prior value was irrelevant. During perceptual discrimination, there was no significant increase in P3 amplitude based on either the previously learned valence or probability of the stimuli. However, there was a significant reduction in P3 latency for stimuli previously associated with more probable outcomes regardless of the valence of those outcomes. These findings suggest that visual items highly probable of an outcome utilize fewer attentional resources, allowing them to be processed at a faster rate.

I. Literature Review

In our environment, we are constantly presented with a wealth of visual information. However, it is impossible for us to be able to perceive or attend to all of this incoming information. One reason for this is that our attentional system is limited in capacity. Information from the outside world constantly competes for our attention, and we must select which information is deserving of our attention through a process called selective attention (Chun & Turk-Browne, 2007). According to Broadbent's (1958) information processing model, we attend to some information while ignoring other information, and hold the stimulus information attended to in a short-term memory store, (i.e., working memory) where the information can be evaluated further or used for decision making (Chun & Turk-Browne, 2007).

1. Information Processing and Attention

As we encounter a visual stimulus from the outside world, we use our eyes to focus that image onto our retina. Our retina contains millions of nerve cells called photoreceptors that absorb and use light to stimulate an electrochemical signal in these receptors. These photoreceptors then send these electrical signals down a large bundle of nerve cells called the optic nerve. Once information arrives at the optic nerve, it travels through the lateral geniculate nucleus, a part of the thalamus that relays visual sensory information to other cortical areas. The lateral geniculate nucleus then passes on the visual information to the primary visual cortex (V1), an area in the brain responsible for complex visual perception, where it can then be processed

further via two informational processing streams, the ventral and the dorsal stream (Hubel, 1978). Visual information that has to do with object recognition enters the ventral stream and is carried from V1 to the temporal lobe to undergo further processing. Information that refers to the spatial characteristics of a stimulus exit V1 through the dorsal stream, which extends to the parietal lobe for further processing (Lamme & Roelfsema, 2000; Ungerleider & Haxby, 1994).

Processing of visual information involves both bottom-up and top-down processing. Bottom-up processing of information begins with neural activity in low-level visual areas and continues being processed further along the visual pathway toward higher order cortices responsible for integrating and making sense of incoming stimuli (Theeuwes, 2010). Top-down processing of information involves processing sweeps from higher-order areas toward low-level visual area . Bottom-up processing typically involves sensory input that captures our attention, while top-down processing reflect characteristics that are relevant to a goal in mind, and thus direct our attention (Connor, Egeth, & Yantis, 2004; Theeuwes, 2010).

When it comes to information processing, researchers equate bottom-up with feedforward processing, and top-down with feedback processing (Lamme & Roelfsema, 2000). The terms "feedforward" and "feedback" adequately represent the directional nature of these pathways. Feedforward processing spreads information from sensory to perceptual stages (Awh, Vogel, & Oh, 2006) and can be illustrated by the way in which the lights of an ambulance influence one's actions. When the lights of an ambulance are flashing, it captures attention by focusing the eye onto the lights. Once these lights are in focus, the information is sent forward to an area that represents the meaning of these lights, and continues to be sent forward until the individual can react to the situation.

Feedback processing extends information from perceptual to sensory stages (Awh et al., 2006) and can best be explained by imagining a goal in mind such as looking for an object among other objects. The information associated with the target object begins with the cortical representation of the object and is sent down this directional pathway until the features of the target object are in focus. The initial processing of a visual stimulus occurs in a feedforward direction, with feedback processing exerting influence as early as 100 ms after (Lamme, 2004; Theeuwes, 2010). Once feedback begins, there is recurrent processing between feedforward and feedback directions that allow one to not only see but also interpret a stimulus (Theeuwes, 2010).

During the initial 100 ms of feedforward processing, it is the salient features of a stimulus, or the characteristics that differentiate that stimulus from its surrounding environment, that capture attention. Attention can undergo feedback processing once captured, allowing for goals to bias where or what attention brings into focus. When information is encountered, it undergoes sensory processing first, and attention is what helps filter relevant from irrelevant information (Gentile & Jansma, 2010). Relevant information that is filtered out of the sensory store and into other cortical areas for further processing is based on a number of factors. The information that is considered relevant or that is successfully selected (filtered) is based on the competition between multiple neural representations (Lamme, 2004). The neurons responsible for these neural representations have an increased firing rate to a stimulus that is either physically salient or attended to (Desimone & Duncan, 1995; Gentile & Jansma, 2010; Lamme, 2004). Information can be filtered due to physical salience in a bottom-up manner, or it can be filtered due to top-down goals. The information that wins this competition gains attentional priority over the other information. Therefore, the prioritization of information is the end result of competition.

2. Attention and Working Memory

Information processing incorporates two overlapping constructs: attention and working memory (WM) (Gazzaley & Nobre, 2012). Attention is the gateway to WM, giving goal-relevant items an advantage when it comes to encoding material into memory (Awh et al., 2006). Attention and WM both have limited capacities, however their limitations differ. Attention selects, filters, and prioritizes information to utilize its limited space efficiently and choose what information will be encoded into memory (Awh et al., 2006; Connor et al., 2004). WM has a limited capacity in the amount of information that can be maintained at one time. Encoding allows information to move into WM, and WM allows information to be updated as well as accessed.

Attention to visual information begins after that information enters a sensory store and before it enters WM (Cowan, 1988). Attention is the mechanism that determines which information from this store will gain access to WM (Cowan, 1988). Once information is held in WM (which consists only of attended items), it is manipulated, evaluated, or elaborated upon in order to answer questions, seek further understanding, or make decisions involving this information (Chun & Turk-Browne, 2007).

3. Attentional Selection

Attention can be captured from exogenous (external) and endogenous (internal) sources. An exogenous stimulus involuntarily captures our attention in the visual field with its distinct characteristics that differentiate it from surrounding stimuli. An example of this type of stimulus could be a deer running out in front of your car, or lights flashing on an ambulance, or any stimulus that demands attention without the conscious directing of attention to it (Yantis, & Jonides, 1984). There are no internal processes such as expectations or personal goals that

manipulate the attention grabbing quality of an exogenous stimulus. Instead, it relies on external physical characteristics to capture attention (i.e., no attached value, meaning, etc.) (Kim & Cave, 1999). This can be assumed from their distinct external physical characteristics that reflect onto the retina and stimulate neurons in the eye. This process is thought to be automatic and beyond one's control (Yantis, & Jonides, 1984).

Endogenous directing of attention happens through feedback processing through the aid of internal goals or expectations that distinguish that stimulus from others in the visual field (Kim & Cave, 1999). An example of endogenous directing of attention would be actively searching for a face amongst a crowd of many other faces. Although the one face that is being searched for has similar features of other faces in the crowd, that face is found faster due to the prior knowledge of that face and its relevance toward a processing goal of finding that person (i.e. mother, child, enemy) (Gazzaley & Nobre, 2012). While exogenous stimuli are thought to be automatic and attention-grabbing, endogenous stimuli can be viewed as guiding the spotlight of attention, such as in a classic "Where's Waldo" task. Having a goal in mind will guide attention to a stimulus with specific attributes that are relevant to reaching that goal (Wolfe, 1994).

4. Selective Attention

It is impossible to attend to all presented stimuli, and therefore the attentional system must select which stimuli are most relevant (Desimone & Duncan, 1995). Selective attention is the ability to attend to relevant information while ignoring, or filtering out, irrelevant information. A stimulus can become relevant through different ways, such as by top-down goals or physical features. Characteristics of a stimulus that differentiate that stimulus from its

surroundings are what make it relevant. Therefore, if a goal is in mind, the attentional system may focus on the items relevant to that goal; however, if there is an item in the same visual field that contains prominent physical characteristics, attention may be focused on that item. Both items compete against each other in what is called biased competition, and it is attention that resolves this competition by selecting which information is in need of attention.

5. Biased Competition

There are neurons in the visual cortex that respond to specific attributes of a stimulus, and the size of the receptive fields on these neurons increase as information is processed further along the visual pathways (i.e., dorsal, ventral). However, the more visual information that is placed on these neural receptors, the less information about any one item we can access, and therefore information related to both visual items compete for space in the receptive fields of the visual processing pathways (Desimone & Duncan, 1995; Wolfe, 1994). When a target object is in mind, WM will maintain the features associated to that target, as that target is now relevant to the observer. However, when there are irrelevant objects that share similar physical features of that target object, the receptive field responsible for that shared physical feature will be overwhelmed and the two objects will be in competition with each other. Whichever object gains attentional priority will ultimately be selected and win the competition (Desimone & Duncan, 1995).

A visual search task is a common experimental model used to manipulate attention and shed light on how attention is biased. In a visual search task, participants are typically searching for one target item among nontarget distractors. When the target contains physical features that are different to the homogenous features of the nontargets, it does not experience high

competition for the receptive fields responsible for those features and is able to be processed fairly quickly. However, when the nontargets share physical characteristics of the target, the receptive fields responsible for these shared characteristics now encounter a competition.

6. Attention Prioritization

As mentioned earlier, stimuli that ultimately win the competitive interaction between two neural representations are the items that gain attentional priority. The salience, or probability, of an item is what gives an item priority.

a. Probability

An item is considered salient when it captures greater attention than the items around it, such as being more probable of an outcome (Parkhurst, Law, & Niebur, 2002). Due to the attention grabbing quality of salient information, this information gains attentional priority (Pessoa, Kastner, & Ungerleider, 2003). For example, the exogenous physical characteristics that discriminate an object from others can make that object attentionally salient. The role that bottom-up Probability plays in our attentional system is best explained by the aforementioned visual search tasks. In these tasks, the targets that have physical qualities independent of the nontargets are considered to be more salient. Treisman and Gelade (1980) found that when the target item was less salient than its surrounding distractors, the time it took to identify the target increased. Not surprisingly, participants were able to identify the target much faster when the target was more salient than the distractors. It is presumed that because salience, or probability, gains attentional priority, targets were able to be processed faster when they were more salient (Treisman & Gelade, 1980).

A stimulus can also be made salient due to top-down endogenous goals or expectations. Top-down salience is dependent on the individual and what may be salient for one person may not be for another. For example, if someone is hungry, food in their environment may be salient to them, while a blanket may be salient to someone else who is cold (Parkhurst et al., 2002). The effect top down salience has on visual attention is demonstrated in a real-world visual search task. In a study by Thompson, Bichot, and Schall (2001), mammographers with varying levels of experience in their field were compared to laypersons in the time it took them to accurately identify breast masses in patients. Mammographic technology was used to display images of breasts on a screen, where the mammographers and laypersons were instructed to search the visual content and identify any breast masses as quickly as possible. The mammographers with the most level of expertise in their field were able to complete this visual search significantly faster than the laypersons or even other mammographers with less experience. These experienced mammographers used their previous knowledge of what breast masses look like, while those with less experience had a difficult time differentiating between the breast masses and visually similar items on the screen. Because the experienced mammographers had prior knowledge of what breast masses looked like, the masses were more salient to those individuals, and thus gained attentional priority. Another reason the experienced mammographers may have been able to more efficiently detect breast masses could be due to their top-down goals of locating these masses. The features associated with breast masses became more salient because they were relevant to a goal.

While bottom-up processing appears to be more easily measured due to the objective quality of an exogenous stimulus, the effects of top-down processing are more complex, requiring interpretation and leaving many questions unanswered as a result of the subjective

characteristics of endogenous salience. Salience is how top-down processing modulates visual attention, but the salience of a stimulus can be established in multiple ways. The present study aims to investigate what effect top-down processing has on visual perception, with salience created by value associations.

b. Value

It is vital to our survival that we notice stimuli that have value to us so that we can more quickly acquire rewards and avoid punishments (Anderson, Laurent, & Yantis, 2012). Visual items become valuable when they convey meaningful information to us, such as a monetary reward or loss. Expected value, defined as the magnitude and probability of a desired outcome, is a term at the crossroads of psychology and economics (Knutson, Taylor, Kaufman, Peterson, & Glover, 2005). Expected value is acquired through learning, which takes place as we encounter the sequential contingencies of a stimulus and the outcome following that stimulus. The strength of the paired association between a stimulus and its outcome increases with each instance it is experienced (Mackintosh, 1975). Establishing the expected value of a stimulus can be explained in a simple formula. The expected value is equal to the expected value given to that association previously, plus a learning rate of how quickly our predictions have been updated, and a prediction error term, measuring the accuracy of the prediction made (Gottlieb, 2012). Neurons in the parietal cortex responsible for encoding the selection of a stimulus are presumed to consistently modulate this value representation and send this information in a top-down direction to the motor cortex, where the individual can then choose the most advantageous action to take in order to maximize their rewards (Gottlieb, 2012). Value prioritizes attention by creating representations in the brain that have consistently paired a stimulus with a desired outcome. Value and reward have been prioritized in attention since infancy. Humans have an innate desire

to acquire valuable stimuli such as food, water, and sex. Prioritizing items that have been learned to acquire value helps the attentional system more efficiently select information and utilize fewer attentional resources (Anderson, Laurent, & Yantis, 2013).

c. Valence

Attention prioritizes information that has a positive or negative valence attached to it, such as punishments and losses or rewards and gains (Buchner, Rothermund, Wentura, & Mehl, 2004; Pessoa & Ungerleider, 2004). It is valuable to be able to distinguish between negatively and positively associated stimuli in our environment so that we can make rapid decisions that keep us away from dangerous situations and close to safety or familiarity (Öhman & Mineka, 2001).

The valence of a stimulus biases our attentional resources towards that stimulus due to the valuable information it provides (Pessoa & Ungerleider, 2004). Valuable information is prioritized above information that is neutral. However, when attentional resources are limited, positively valenced stimuli are prioritized in the attentional system over negatively valenced stimuli (Raymond & O'Brien, 2009). In a study investigating the effects of valence on attention, participants made associations between stimuli (faces) and monetary values during a learning phase. Faces associated with specific monetary outcomes were then incorporated into an attentional blink (AB) task. In an AB task, a series of visual images rapidly flash on a computer screen one after the other. The participant is instructed to focus their attention on two visual targets. Because attentional resources are allotted to the first target, participants typically do not report recognition of a second target that appears in close proximity to the first target. In other words, attention "blinks" during the display of the second target. When the time between the

presentation of the first and second target was short, valence determined the AB effect. More specifically, when attentional resources were limited, the items previously associated with loss or neutral outcomes were not recognized as often as items that were associated with gain outcomes. This alone shows the impact value has on attention. Even though the task was completely unrelated to the associated value of the stimuli, the previously learned value impacted the processing of these stimuli (Raymond & O'Brien, 2009). These findings strengthen the existing argument that valence, as a learned value, influences attention prioritization.

Research on emotion and attention gives great insight as to how positive and negative valences in the form of emotions influence attention as well (Pessoa & Ungerleider, 2004). To test the impact emotional valence has on attention, researchers used a modified Stroop task, a task that displays color words either in their color or in a different color. This particular Stroop task contained negative adjectives, positive adjectives, and neutral adjectives. Participants had longer reaction times when naming the color of the valenced words than the neutral words, and had an even longer reaction time when naming the negative adjectives compared to the positive adjectives (Pratto, 1994 as cited in Buchner et al., 2004). In a Stroop task, the longer the reaction time in naming the color of the word, the more interference one is experiencing. The argument could be made that these individuals are subjected to interference by virtue of the valenced words capturing attentional resources.

Studies indexing attention through reaction times that involve emotionally significant stimuli help build a strong case for the effect of value on attention. Emotions are innate and their values do not have to be learned in a previous task. Therefore, many experiments utilize emotionally charged stimuli to represent valence. The previous experiment demonstrates the ability of valenced stimuli to capture attention. Just as the faces associated with positive

outcomes in the previous study allow for better recognition and thus capture attention, the adjectives associated to negative emotions also captured attention, which is shown through increased reaction times when naming the color of those specific adjectives.

There is ongoing debate as to how valenced stimuli are processed. Some researchers believe that valenced stimuli are not automatically processed, but instead they shift our attentional resources to the valenced information (Buchner et al., 2004; Rothermund, 2003). In other words, valence does not necessarily demand attention, but requires our attention in order to have any influence on the processing of information (Pessoa & Ungerleider, 2004). However, there also exists research in support of the idea that valence does not require attention and is processed automatically (e.g., Bargh & Tota, 1988; Meng, Yuan, & Li, 2009)). In an event-related potential (ERP) study, which measures the electrical brain activity during a specific event, researchers found increased negative activity in the N2 component when participants were shown negatively-valenced images as opposed to neutral images. Importantly, this activity was elicited at 150-200 milliseconds post stimulus representation, a time period that represents unconscious visual awareness of a stimulus (Del Cul, Baillet, & Dehaene, 2007; Meng et al., 2009). If valenced information is processed at such an early stage, it may have an impactful top-down influence on attention by automatically choosing which information in our visual field is important and deserving of limited attentional resources.

d. Reward

As previously stated, human beings have an inherent drive to acquire the maximum reward in any given situation. By cause of this, individual's' attentional resources have adapted to give rewarding information a perceptual advantage to make the processing of vast amounts of

visual information more efficient (Anderson et al., 2013). Studies repeatedly show that when a stimulus is learned to have a rewarding value, it is prioritized in our attentional system beyond other valued stimuli (Anderson et al., 2012; Anderson et al., 2013; Lee & Shomstein, 2010; Raymond & O'Brien, 2009; Shomstein & Johnson, 2013). Della Libera and Chelazzi (2009) demonstrated the effect reward has on attention prioritization with an object identification task. Participants engaged in a learning task prior to the object identification task to associate certain shapes with rewards or losses.

In the experiment, participants were shown a cue (red or green square) followed by a presentation of a fixation cross in the center of the screen. Two shapes were shown to the left of the fixation cross, one red and one green. The shapes overlapped each other while remaining fully visible. To the right of the fixation was one shape in black. Participants were instructed to judge if the shape on the right of the fixation in black matched the target. The target was defined as the shape on the left of the fixation that matches the color of the square prior to its appearance. Participants must filter out the overlapping distractor shape in order to complete the task.

In the training phase, participants were given a monetary reward for correct judgment trials. Some shapes had a higher probability of reward (80% of correct trials) while others had a low probability of reward (20% of correct trials). Several days later, participants completed the same study with the absence of reward. This testing phase consisted of the exact same shapes in the training phase. The dependent measure was the reaction time in making a correct judgment.

The target shapes previously associated with a high probability of reward in the training phase that became distractors in the experimental task made judgment reaction times increase significantly, while shapes previously associated with a lower probability of reward in the

training phase that became distractors in the experimental task showed no increase in reaction times when making a judgment. Reaction times provided strong evidence that reward does become prioritized in the attentional system (Della Libera & Chelazzi, 2009).

Attentional bias within our visual system has also been associated with reward in studies involving drug users and addicts (Lubman, 2000). Methadone-dependent and control participants differ substantially in their performance on a probe detection task. A probe detection task involves the presence of two pictures on a screen with each picture corresponding to a specific location (left, right). Following the presentation of the two pictures is a probe, which in this experiment is a dot, in one of the picture's locations. The participant must choose as quickly as possible the location in which the probe appeared. The pictures in the task illustrated by Lubman and colleagues (2000) varied between control pictures, drug-related pictures, and neutral pictures. The participants who were methadone-dependent showed significantly faster reaction times than controls to probes replacing the location of drug-related pictures than any other pictures. It is presumed that these drug-related pictures cue reward for the addicts and thus bias their attention to that location.

Another study conducted by Gross, Jarvik, and Rosenblatt (1993) provides additional evidence for reward related attentional bias through a Stroop task. In this task, participants were all addicted to nicotine; however, half of them abstained from smoking any nicotine for 12 hours. For this experiment, the color words were replaced with neutral words or smoking-related words, and participants were instructed to name the color of the word as quickly as possible. As expected, the addicts who had sustained from smoking any nicotine for at least 12 hours had significantly slower reaction times than the other participants to the smoking-related words than the neutral words. It is suggested that this interference is due to the meaning of these smoking-

related words capturing attention. Due to the rewarding value the smoking-related words have on these participants, they are more likely to capture attention. If the participant values the actual word, he or she will focus more on the word and not the color of the word. Neutral words have no rewarding value to these participants and thus do not require attentional resources, thus allowing for attention to be allocated to the color of those words. Participants who have abstained from smoking will find smoking-related words more rewarding than those that have just smoked nicotine and thus already acquired their nicotine associated reward (Gross et al., 1993).

In visual perception, covert attention is defined as the rapid processing of items in the foveal region compared to those items in the periphery (Henderson, Pollatsek, & Rayner, 1989). Several visual experiments illustrate that covert attention facilitates eye movements toward an object (Deubel & Schneider, 1996; Kowler, Anderson, Dosher, & Blaser, 1995). In order to focus and sharpen an image, the image must stimulate the fovea, a part of the eye that is responsible for acuity. Subsequently, it should be of no surprise that the eye fixates on locations consisting of high attentional priority (Thompson & Bichot, 2005). Anderson and Yantis (2012) measured eye movements during a judgment task involving reward. In the learning phase, the participants were shown an array of different colored circles with a single bar enclosed inside each of them. The red colored circle was the target, and if the participant correctly identified the bar in the target circle as being either vertically or horizontally oriented, they would acquire a monetary reward. In the testing phase following the learning phase, all of the same colored circles were present, except this time one of the circles was a different shape, such as a diamond. Participants were given the same instructions, but the target in the test phase was no longer the red circle, instead it was the blue diamond. Upon evaluating participants' eye fixations during the

testing phase, Anderson and Yantis (2012) discovered that the distractor in the testing phase responsible for monetary value in the learning phase was far more likely to be fixated on than the target. These results were supported by behavioral data collected during the same experiment. In the testing phase, participants had slower reaction times when the value-associated circle was present. Based on the aforementioned study and its conclusions, it appears as though items that have been previously associated with reward bias spatial attention allocation and are even capable of doing so when they are task-irrelevant and no longer possess rewarding value (Anderson et al., 2013).

II. Measuring Top-Down Influences on Attention

To be able to measure the effect of attention on the amount of attentional resources being allocated, or on the speed of processing this information, relevant to attention, the instrument used must have exceptional temporal resolution. ERPs reflect ongoing brain activity centered on a particular event in time and are very sensitive to the timing of mental processes (on the order of ms). ERPs are extracted from continuous data collected using electroencephalography (EEG). EEG measures the electrical activity emitted from clusters of nerve cells, or neurons, in the cerebral cortex within one to five milliseconds of firing (Gevins, Smith, McEvoy, Leong, & Le, 1999; Hulbert, 1947). Electrodes are applied externally onto the scalp and amplify the electricity caused by the firing of neurons. The activity recorded from the EEG is then represented in waveforms (Hulbert, 1947). The EEG recording collects data from a variety of neurons that are firing in response to many different events. In order to more clearly identify the electrical pattern of activity responsible for a specific event or occurrence, researchers average all of the electrical activity that occurs centered around that event. The averaged waveform that emerges from this process is called an ERP. ERPs are an important measure in the field of neuroscience due to their

continuous recording of neural activity in the brain, making it easier to identify which phase in perceptual or post-perceptual cognitive processing has been influenced by an experimental manipulation.

Years of research using ERPs have provided a wealth of knowledge regarding the meaning of these common waveforms and in which instances they are observed. These waveforms are comprised of positive and negative deviations in voltage occurring at different times throughout the processing of an event. These deviations reflect the difference in voltage from baseline, or prestimulus activity. Therefore, the P components are above baseline, while N components are below baseline. Each positive peak in the wave is followed by a negative peak, and thus P1 comes prior to N1. The number corresponds to the timing the peak took place. For example, the P1 component, or P100, is a positive deflection that begins at 100 milliseconds post stimulus onset. While this component is detected early on in the processing stages, it should come as no surprise that it is responsible for the processing of sensory information, or exogenous features of a stimulus. However, the P3 component (positive peak beginning at 300 milliseconds) is often influenced by the endogenous features of a stimulus, as it occurs later in processing (Luck, 2005).

The interpretation of these components typically lies in the size and measurements of the amplitude and latency of a particular component. Amplitudes are used to measure the size of the underlying component (Sur & Sinha, 2009). For the P3 component, for example, a larger amplitude typically reflects an increase in the amount of cognitive effort utilized during a distinct event in time. Particular to P3, the latency reveals the difficulty of the task. For example, if the P3 latency is short for a participant during a trial, this would mean the task is relatively easy or that the participant has performed exceptionally well with little mental effort on a difficult task

(Sur & Sinha, 2009). The key to interpreting the meaning of these latencies and amplitudes lies in the theoretical framework that underlies the study at hand.

The P3 component is one of the most complex to interpret because there is no universal agreement on what the P3 wave actually reflects (Luck, 2005). Studies have shown that it reflects the updating of one's representation of the surrounding environment, while others believe it is an index of attention. A multitude of studies have helped solidify the attention allocation hypothesis of the P3. Isreal, Chesney, Wickens, and Donchin (1980) interpret the P3 amplitude as an index of attention by discovering that a subject must attend to a stimulus in order to elicit a P3. When participants were given a concurrent task of visually tracking items on a screen while simultaneously counting tones presented to them, the P3 amplitude decreased significantly compared to when participants were solely tracking visual stimuli. Due to the reduced attention given to any one task, the P3 wave logically decreased.

The P3 component is also cited in studies as being related to reward processing (Pfabigan et al., 2014; Yeung & Sanfey, 2004). Yeung and Sanfey (2004) conducted an experiment to measure the P3 component in participants engaged in a virtual gambling task. Participants were shown two different colored squares with one on either side of a central fixation point. The two squares were to mimic two randomly selected cards in a deck of four cards (red, green, blue, purple). The participants were instructed to choose any square at random, and were then given feedback of their monetary gain or loss for choosing that specific card. After receiving feedback on their selection, the monetary value of the other card appeared on the screen to show the participant what the alternative outcome would have been if they had chosen the other card. Two of the cards were always respective of large outcomes (gains or losses) while the other two cards were always associated with small outcomes. The researchers found a significant main effect of

increased P3 amplitude for magnitude of outcome. This means that the peak of the P3 component was largest in response to larger outcomes than smaller outcomes, whether gains or losses, when receiving feedback on their chosen card. Therefore, the argument can be made that the cards associated with greater outcomes allocated more attentional resources.

There was no significant effect of valence on the P3 component for this particular proportion of Yeung and Sanfey's (2004) study. However, when observing the alternative outcome of the unchosen card, there was not only a main effect of magnitude and of valence on the P3, but also an interaction between the two. The P3 amplitude increased as larger alternative outcomes were observed, particularly when the larger outcomes were positive values. Due to the increased P3 component in reward processing of attained and unattained outcomes, it is possible that the P3 is involved in the coding of reward, whether that reward is obtained or not (Yeung & Sanfey, 2004).

In a similar study conducted by Goldstein and colleagues (2006), the P3 amplitude was measured in response to varying incentive values in a "Go/No-Go" task. A Go/No-go task is when the participant must push a button or lever in response to the onset of a stimulus in the "Go" condition, or the participant must refrain from responding in the "No-go" condition. Participants were shown on a screen the amount of monetary reward (0¢, 1¢, or 45¢) earned if they accurately complete the trial. Once participants are shown how much money they can potentially earn, they are shown a picture that is either indicative of a "Go" condition or a "No-go" condition. Following the presentation of the picture, a target appears and the participant must respond to the target according to the present condition. When participants engaged in a trial where the reward was 45¢, their P3 amplitude (measured at the onset of the image cueing for a "Go" or "No-go" condition) significantly increased in comparison to trials with a potential

reward of 0¢ of 1¢. The amplitude of the P3 wave correlated with the reward values with the largest peak to the cued stimuli occurring in response to the largest value condition and the smallest peak in response to the smallest value condition.

A third study that is most convincing of the influence of reward on P3 correlates ERP data with functional magnetic resonance imaging (fMRI) data (Pfabigan et al., 2014). An fMRI is another noninvasive instrument used to measure brain activity. It is presumed that neurons that are active and firing utilize blood, and blood requires oxygen. This brain activity is analyzed using a BOLD (blood-oxygenation level dependent) signal and the stronger the BOLD signal, the greater brain activity in that specific area. In this particular study, demonstrated by Pfabigan and colleagues (2014), participants were given a monetary incentive delay task in order to measure ERPs and fMRI activity in the anticipation phase of reward. Participants were shown a cue associated with either a monetary gain or avoidance of a loss on a screen and were then instructed to complete the trial correctly to obtain that reward. A question mark replaced the cue and preceded a target stimulus (black square) in which participants were required to respond to as quickly as possible. Results from the fMRI BOLD signals displayed increased brain activity in areas associated with reward. The observed ERP data revealed that the largest amplitude in the P3 component was in response to the gain incentive cues compared to the loss and neutral cues. However, the P3 still had increased amplitude for loss incentive cues in comparison to neutral cues as well. Most interestingly is the correlation the researchers noticed between the ERP and the fMRI data. The larger the P3 amplitude, the more pronounced the BOLD signal in the reward related areas of the brain (Pfabigan et al., 2014).

Research also supports an effect of learned probability on attention and the speed of processing, facilitating in the theory behind measuring probability effects via the P3 component.

Using the same learning task and stimuli as Raymond and O'Brien (2009), O'Brien and

Raymond (2012), found significant effects of learned probability on the processing speed of

these learned stimuli when subsequently encountered in a backward masking task. Participants

associated face stimuli with specific monetary wins or losses of high or low probability

occurrence. Once participants learned the expected values of these particular faces, the same

faces were then shown individually (intermixed among a set of novel faces) for a brief period of

time (~20 – 100 ms) and then replaced with a visual mask. Participants were able to make an

old/new judgment for faces previously associated with high probability after a duration

significantly shorter than the faces that were not highly probable of an outcome or that were

novel. Interestingly, there was no effect of valence on the amount of time needed to view the

face before being masked (O'Brien & Raymond, 2012).

III. Current Study

The current study is interested in the influence that learned value has on the amount of

attentional resources utilized in processing stimuli and the speed of processing stimuli. The P3

ERP component is the tool that will be used to indicate whether value has effectively influenced

the processing speed or allocation of attentional resources of a stimulus. As mentioned earlier,

reward can capture one's attention and thus has an effect on the size of the P3 wave. If the

hypothesis of this study is correct, there should be significantly larger amplitudes for the

rewarding versus punishing stimuli and for stimuli that are of high probability compared to low

probability due to the additional attention these stimuli require. Previous research supports the

idea of P3 latency indexing stimulus-processing speed (Kutas, McCarthy, & Donchin, 1977).

Therefore, there should also be reduced latencies for stimuli associated with high probability

than that of low probability, suggesting that highly probable items are processed faster (O'Brien & Raymond, 2012).

Participants first engaged in a learning task where they associated particular faces with a monetary gain (reward), a monetary loss (punishment), or no monetary outcome. In addition to valence, probability was also manipulated. Some faces had a rewarding or punishing value 20% of the time (and no outcome 80% of the time); other faces had these values 80% of the time (and no outcome 20% of the time). The valence of a stimulus in this study is referred to as Gain, Loss, or Neutral, while the probability of that valence outcome is referred to as High or Low. The combination of these two resulted in five expected values: High Gain, Low Gain, High Loss, Low Loss, and Neutral.

After participants completed the learning task, EEG was then recorded during completion of a perceptual discrimination task that incorporated the stimuli previously associated with reward or punishment. In the perceptual discrimination task, participants viewed the previously learned faces and indicated which direction the faces were tilted (left, right). As highlighted earlier, it is hypothesized that faces that were previously associated with a monetary gain or loss, and/or of high probability will elicit a P3 wave that has an increased amplitude in comparison to when the participants are making a perceptual decision for the faces that did not increase or decrease their monetary value and/or have a low probability. This would mean that in congruence with previous literature, stimuli that have been previously associated with value continues to influence information processing even when the value of that stimulus is no longer relevant. Additionally, one could presume this effect due to items that are valuable having an attention capturing or grabbing quality that allows them to win in biased competition. This can

be evidenced by the increased amplitude in P3, which has not only been shown in increased attention but also with sensitivity to reward and value in general.

If the aforementioned theory supporting the idea of P3 latency indexing stimulus-processing speed is correct, there should be a significantly smaller latency in either the valence or high probability conditions. A reduced latency toward stimuli that are of rewarding value (High Gain, Low Gain) compared to punishing value (High Loss, Low Loss) regardless of probability, should be present if rewarding stimuli truly requires a reduced amount of time to process. However, it is possible that there will instead be an effect of probability. A reduced latency for stimuli that are highly probable (High Gain, High Loss) regardless of valence, as opposed to stimuli that provide an outcome less frequently would provide evidence congruent with the literature regarding processing speed and salience (O'Brien &Raymond, 2012; Treisman & Gelade, 1980). This would suggest that the brain can process information that is more probable of an outcome at a faster rate than information that is less probable of an outcome (Kutas et al., 1977).

IV. Method

1. Participants

Seventy-three right-handed undergraduate students between ages 18-31 ($M = 19.40$) attending the University of South Florida were given course credit for their participation in the study. All participants gave informed consent prior to their participation. Participants were not included in the final sample if they did not meet criteria for learning, performed below chance in the perceptual discrimination task, or had unusable EEG data (as detailed below). A final sample size of thirty-nine was used in the data analysis.

2. Stimuli

The faces used in both tasks were static computer-generated (GenHead 1.2; Genemation, Inc., Manchester, England), gray-scale faces of young adult males and measured 2.9° x 3.6°. The same stimuli used in both tasks (described below) were presented on a Dell Optiplex monitor (51 cm) at a viewing distance of 52 centimeters. All tasks and stimuli were presented using E-prime 2.0 (Schneider, Eschman, & Zuccolotto, 2012).

3. Learning Task

In this phase of the experiment, two faces were shown simultaneously on the computer screen with one face located in the top center of the screen and the other in the bottom center of the screen. Participants were instructed to press either the "t" key for top, or the "b" key for bottom upon the display of the faces. On the very first trial, participants chose a face at random. After their selection, the face they chose either awarded them money (Gain), took money away (Loss), or did not affect their total outcome (Neutral). Some faces were more likely to award money than others (80% of the time, 20% no outcome) while other faces were less likely to award money than others (20% of the time, 80% no outcome), and likewise some faces were more likely to take away money (80% of the time, 20% no outcome) while other faces were less likely to take away money (20% of the time, 80% no outcome). Faces in the Neutral condition always resulted in no monetary outcome. There were 200 trials for each of the Gain, Loss, and Neutral conditions, equaling a total of 600 trials. This task was untimed and participants chose the faces at their own pace. Over time, participants were expected to learn the values of these faces. Participants who chose the optimal face in at least 55% of the last 30 trials for each condition were considered to have learned the values of the faces. Twenty-two participants were

not included in the final sample because they did not meet criterion for learning. This portion of the experiment was analyzed behaviorally; there is no EEG recording for this data.

4. Perceptual Discrimination Task

Upon completion of the learning phase, participants began a perceptual discrimination task that incorporated the same faces in the previous learning phase. In this task, participants were instructed to focus on a fixation cross in the center of the screen. On each trial, one of the faces from the learning phase was presented in either the top left or the top right of the screen. Each face was either tilted 45 degrees to the left or the right. Participants were instructed to press the "1" key if the face was tilted to the left and the "4" key if the face was tilted to the right. There were a total of 300 trials in this portion of the experiment, evenly distributed between conditions (High Gain, High Loss, Low Gain, Low Loss, Neutral). Within each condition, 150 trials had faces tilted to the left, and 150 trials had faces tilted to the right, and within the 150 trials, 75 of those trials presented faces in the left visual field while the additional 75 trials presented faces in the right visual field. There were a total of 1200 trials. This task contained 12 blocks, with 100 trials within each block. There was a break between each block and participants were instructed to take as much time as needed during each break. Participants were instructed to respond to the presentation of the stimulus as quickly as possible. Ten participants were not included in the final sample because they performed below chance on the discrimination task.

5. EEG Recording

Continuous EEG data were acquired using a 128-channel (including eye channels) EGI system (Electrical Geodesics, Inc.) sampled at 250 Hz, referenced to the CZ electrode. All EEG data were filtered offline with a 0.1 Hz high-pass filter and a 20 Hz low-pass filter. Waveforms

were segmented into 1000 millisecond epochs spanning 200 milliseconds before presentation of a tilted face to 800 milliseconds after the presentation. Individual ERPs were baseline corrected over the 200 millisecond pre-stimulus period and referenced to averaged mastoids. Netstation 5.0 (EGI, USA) Artifact Detection tool marked channels exceeding 200 µV as bad for the entire segment. After running an algorithm detecting and discarding bad eye channels, Netstation 5.0 Perform Inferences tool marked any threshold-violations greater than 140 µV as eye blinks and greater than 55 µV as eye movements in the remaining data. Artifact Detection also marked channels bad for all segments if the channel was bad for at least 20 percent of segments. Segments were marked bad if they contained more than 10 bad channels, an eye blink, or an eye movement. NetStations's Bad Channel Replacement tool replaced bad channels in good segments with data from surrounding electrodes. All bad channels were excluded when referencing was averaged to the Mastoids. Mean amplitude and peak latency for the P3 were taken from oddball-minus-frequent difference waves (collapsed across visual field) 300-356 ms post-target onset at midline parietal electrode Pz.

6. Data Analysis

Mean latencies and amplitudes were first analyzed in a one-way analysis of variance (ANOVA) with expected value (High Gain, Low Gain, High Loss, Low Loss, Neutral) as the within-subjects factor, followed by a two-way repeated-measures ANOVA with valence (Gain, Loss) and probability (High, Low) as the within subjects factors. Greenhouse-Geisser corrections were used where applicable. Bonferroni *post-hoc* analyses were used to follow-up significant effects in ANOVA analyses. Six participants were not included in the data analyses because of unusable EEG data.

V. Results

1. Behavioral Data

a. Learning Task

On average, participants correctly chose the High Gain face 87.36% (SD = 0.12) of the time, the Low Loss face 76.75% (SD = 0.12) of the time, and chose one of the two Neutral faces 42.30% (SD = 0.28) of the time across the last thirty trials during the learning task (Table A2; Figure A1). A paired samples t-test was conducted to compare the learning rates for 'Gain' and 'Loss' faces. Participants learned the 'Gain' faces significantly better than the 'Loss' faces, $t(44)$ = 5.90, p = <.001 (Table A1).

b. Perceptual Discrimination Task

Participants performed at 94% (SD = .03) accuracy for all five (High Gain, Low Gain, High Loss, Low Loss, Neutral) conditions. There was no significant effect of expected value on behavioral performance (Table A3; Figure A2), $F(2.89, 121.40)$ = 0.09, p = 0.960. Means and standard deviations are shown in Table A4.

2. ERP Results

Figure 3 shows the grand average of all subjects included in the final analyses (N= 39) at the midline parietal electrode (Pz) during the perceptual discrimination task in which the time window (300-356 ms) was decided on for further analyses of amplitude and latency.

a. P3 Amplitude

There was no significant effect of expected value on mean amplitude (see Table A5 and Figure A4), $F(3.19, 102.16) = 1.91$, $p = 0.13$. Means and standard deviations are shown in Table A6. When comparing the effects of valence and probability on P3 amplitude, there was insufficient evidence to conclude that valence (Figure 5) $F(1, 32) = 0.62$, $p = 0.42$, or probability (Figure A6) $F(1, 32) = 0.62$, $p = 0.44$, had an effect (Table A7). Means and standard errors for valence and probability can be found in Tables A8 and A9 respectively. There was no interaction between probability and valence on mean amplitude.

b. P3 Latency

There was no significant effect of expected value on mean latency (Figure A8), $F(3.29, 105.17) = 1.88$, $p = 0.13$. Means and standard deviations are shown in Table A10. However, when comparing the effects of valence and probability on latency (Table 12), there was no significant effect of valence, $F(1, 32) = 1.09$, $p = .304$ (Table A13; Figure A9), but there was a significant main effect of probability, $F(1, 32) = 5.63$, $p = .024$ (Table A14; Figure A10), with the high probability condition ($M = 328.06$, $SE = 3.28$) eliciting significantly reduced mean latencies in P3 compared to the low probability condition ($M = 333.76$, $SE = 3.15$). There was no

significant interaction of valence and probability on mean latency (Figure A11), $F(1, 32) = .01$, $p = .914$.

VI. Discussion

In this study, a forced-choice learning task was used to imbue novel stimuli with different expected values. Faces that have never been seen before by the participants were associated with positive and negative expected values of high and low probability depicted through monetary outcomes. The purpose of this study was to investigate the effect of value learning on the speed of processing and the amount of resources allocated to that processing. In this particular study, value is considered the valence, probability, or combination of both that a stimulus holds. In most studies, the value of valence is manipulated through emotion. However, to eliminate any previous influence learning might have on value, learning was established with novel stimuli in this experiment. Although the stimuli used were faces, there were no emotions expressed. If a participant met learning criteria, they learned to associate each face with either a gain, loss, or neutral monetary value. For each loss- and gain-associated face, they learned to associate it with either a high (80%) or low (20%) probability of outcome. Once participants completed the learning task, they completed a perceptual discrimination task that incorporated the same faces from the previous task with learned value now task irrelevant.

The goal of the study was to determine whether the learned value of a stimulus has an effect on the attentional processing of that stimulus when reencountered. The ERP component we looked at as an index of attention was the P3. The amplitude (or magnitude) of the P3 is associated with the amount of attentional resources allocated to a stimulus, or event. The latency (or duration) of the P3 corresponds to the processing speed of a stimulus, or event. Therefore,

both elements were critical to examine when exploring the effects of attentional capture, selection, biased competition, and other facets of attentional top-down processing. The a priori hypotheses that we expected to find are as follows; a) there will be a significant increase in P3 amplitude for valence (gain vs. loss faces), b) there will be a significant increase in P3 amplitude for probability (high vs. low probability faces), c) there will be a significant increase in P3 latency for valence, d) there will be a significant increase in P3 latency for probability.

Having a significant increase in P3 amplitude for the value of valence or probability would suggest that items of either valence or of probability allocated more attentional resources, or effort. This could be interpreted as valenced or items of probability gaining attentional priority or having won biased competition. Previous literature has provided evidence that stimuli of high probability have elicited a larger P3 amplitude than items that are less probable (Kok, 2001). In our results, we did not see a significant increase or decrease in P3 amplitude for probability or valence. While the P3 ERP component is one of the most researched components in psychology, it still has many different interpretations due to its complexity. Although one would presume that more difficult tasks require more attention and processing effort, many studies have shown a decrease in P3 amplitude when the difficulty of a task increases (Kok, 2001). This is an interesting finding as it could explain the null effects found in our study. Perhaps there was an increase in amplitude due to probability, but the task also reached a point of difficulty that in turn caused the amplitude to decrease as well. If this were the case in our study, any effects would dissipate.

While none of our apriori hypotheses held true for the effects of value learning on the P3 amplitude, or amount of resources given to a stimulus, this is not the case when inspecting P3

latency. When it comes to valence (gain, loss) there is no significant increase in P3 latency; however, there is when it comes to probability (high, low). Regardless of the valence of the faces, faces that were associated with high probabilities (high gain, high loss), had a decreased P3 latency. As previously mentioned, the latency of the P3 component translates to the processing speed during a task. Therefore, information that is highly salient is processed at a more rapid speed than information that is not as salient. This fits well with literature regarding the effect of salient features in a visual search task. As discussed earlier, Treisman and Gelade (1980) discovered that participants had faster reaction times to targets in a visual search that had features more salient than the distractors. Also, participants had decreased reaction times to targets when they had features less salient than the distractors. Although this study focuses purely on bottom-up salience, it is still salience nonetheless. In a study by Raymond and O'Brien (2009), participants exhibited better recognition for items of high-probability in an AB task, regardless of valence. In an AB task, the second target (T2) should not be recognized due to our attention 'blinking' during that target because it is presumed to still be processing the first target, The fact that T2 was recognized only when it consisted of a salient stimulus, provides evidence that salience, or probability, does have an attention-capturing quality. Raymond and O'Brien (2009) provide evidence of top-down salience impacting attentional capture.

In conclusion, salient information such as information that is more probable of an outcome is processed more quickly because it may capture attention. The salient features of these faces were endogenous, meaning they were salient due to the relevant information they provided, and not due to any physical characteristics that demanded attention. During top-down processing, the salient features were processed quick enough in order to have an effect on feedback processing. Therefore, the learned associations of these faces (salience) were relevant enough to

influence the speed of feedback processing with the aid of internal goals in mind. According to the theory of selective attention (Triesman & Gelade, 1980), we must select information that is relevant while ignoring, or filtering out, information that is irrelevant. If a goal is in mind, the attentional system focuses on the items relevant to that goal and selects those items for further processing. For this reason, we can presume that salient stimuli are more relevant than non-salient items regardless of valence. Positive and negative outcomes do not provide information as meaningful as the magnitude of those outcomes. From the perspective of biased competition, information that is salient or more probable of an outcome, wins the competition between items that are less salient and thus, gains attentional priority.

A real world example of how these findings implicate processing could be that we will attend to an item in our visual field that is more informative of an outcome no matter whether the outcome is positive or negative. This is interesting because it tells us that we value the likelihood of a negative outcome just as much as we value the likelihood of a positive outcome. For example, when choosing between two items, you are just as interested in the item that will provide you the greatest loss as you are in the item that will provide you with the greatest gain.

Future replication should explore these effects in a task that is less difficult than the perceptual discrimination task. In the task that was used in the current experiment, it is possible that the faces were shown at a rate that was too fast for accurate comprehension, or that the faces were too distorted to the participant when they were tilted. If the difficulty of the discrimination task could be reduced, then we may see an effect of learned value on P3 amplitude. It would also be beneficial to manipulate task difficulty. Perhaps there could be a between-subjects variable of task difficulty that would allow us to see if the theory of task difficulty washing out attentional

capacity effects has any merit. It would also be helpful to study the effect of bottom-up versus top-down salience on the rate of processing to see if top-down influences are powerful enough to gain priority over bottom-up salience. All in all, the effect of salience on attention seems to be replicated repeatedly throughout the P3 literature. However, most studies indicate the influence of salience on P3 amplitude, while our study is more unique in its finding of the effects of salience on P3 latency.

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Appendices

Appendix A: Tables

Tables

Table A1. *Paired-samples t-test of 'Gain' and 'Loss' values*

	Mean	SD	SEM	t	df	Sig. (2-tailed)
Gain - Loss	.11	.12	.02	5.90	44.00	.000

Table A2. *Means and standard deviations for learning rates of 'Gain' and 'Loss' values*

	Mean	N	SD
Gain	.87	45.00	.12
Loss	.77	45.00	.12

Table A3. *One-way analysis of variance for behavioral accuracy of value*

	SS	df	MS	F	Sig.
Value	4.37E-05	2.89E+00	1.51E-05	.094	.960
Error(Value)	1.95E-02	1.21E+02	1.61E-04		

Table A4. *Means and standard deviations for behavioral accuracy of value*

Value	Mean	SD	N
HG	.94	.04	39
LG	.94	.03	39
HL	.94	.03	39
LL	.94	.03	39
N	.94	.03	39

Table A5. *One-way analysis of variance for mean amplitude of value*

Source	SS	df	MS	F	Sig.
Value	9.022	3.192	2.826	1.909	0.129
Error(Value)	151.221	102.16	1.48		
Total	160.243	105.352	4.306		

Appendix A continued

Table A6. *Means and standard deviations for mean amplitude of value*

Value	Mean	SD	N
High Gain	3.91	2.52	33
High Loss	4.26	2.48	33
Low Gain	3.95	2.72	33
Low Loss	3.91	3.08	33
Neutral	3.53	2.39	33

Table A7. *Analysis of variance for mean amplitude of probability and valence*

Source	SS	df	MS	F	Sig.
Salience	.785	1	.785	.624	.435
Error (Salience)	40.259	32	1.258		
Valence	.857	1	.857	.662	.422
Error (Valence)	41.380	32	1.293		
Salience * Valence	1.285	1	1.285	1.442	.239
Error (Salience*Valence)	28.512	32	.891		
Total	113.078	99	6.369		

Table A8. *Means and standard errors for mean amplitude of valence*

Valence	Mean	Std. Error
Gain	3.928	.439
Loss	4.089	.469

Table A9. *Means and standard errors for mean amplitude of probability*

Salience	Mean	Std. Error
High	4.085	.424
Low	3.931	.482

Appendix A continued

Table A10. *Analysis of variance for mean latency of value*

Source	SS	df	MS	F	Sig.
Value	1374.061	3.287	418.074	1.884	.131
Error(Value)	23342.739	105.173	221.947		
Total	24716.800	108.459	640.021		

Table A11. *Means and standard deviations for mean latency of value*

Value	Mean	Std. Deviation
HG	326.6667	21.85559
HL	329.4545	21.79032
LG	332.6061	18.97686
LL	334.9091	20.30450
N	332.7273	19.65845

Table A12. *Analysis of variance for mean latency of probability and valence*

Source	SS	df	MS	F	Sig.
Salience	1071.030	1	1071.030	5.629	.024*
Error (Salience)	6088.970	32	190.280		
Valence	213.818	1	213.818	1.091	.304
Error (Valence)	6274.182	32	196.068		
Salience * Valence	1.939	1	1.939	.012	.914
Error (Salience*Valence)	5286.061	32	165.189		
Total	18936.000	99	1838		

* $p < .05$

Appendix A continued

Table A13. *Means and standard error for mean latency of valence*

Valence	Mean	Std. Error
Gain	329.636	3.110
Loss	332.182	3.328

Table A14. *Means and standard errors for mean latency of probability*

Salience	Mean	Std. Error
High	328.061	3.279
Low	333.758	3.148

Appendix B: Figures
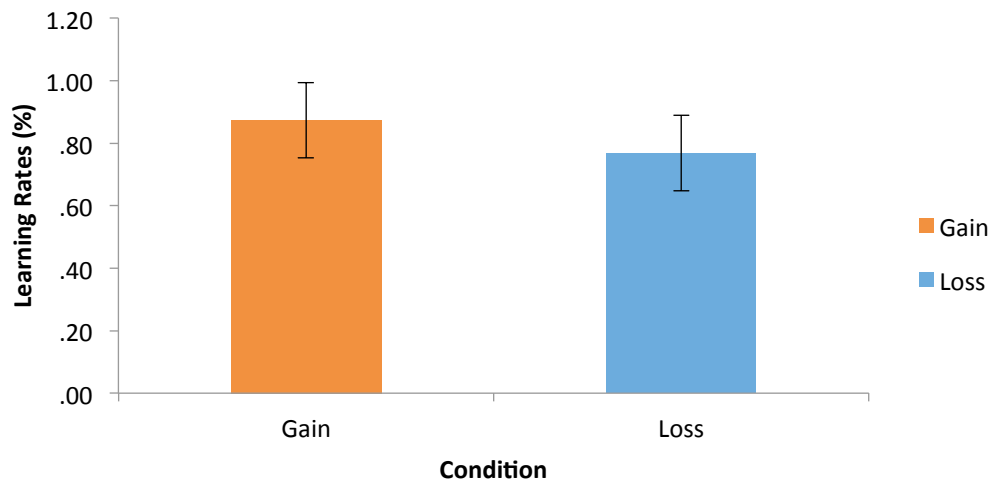
Figure A1. *Learning rates as a function of 'Gain' and 'Loss' values with standard deviations as standard error bars (SD +/- 1).*
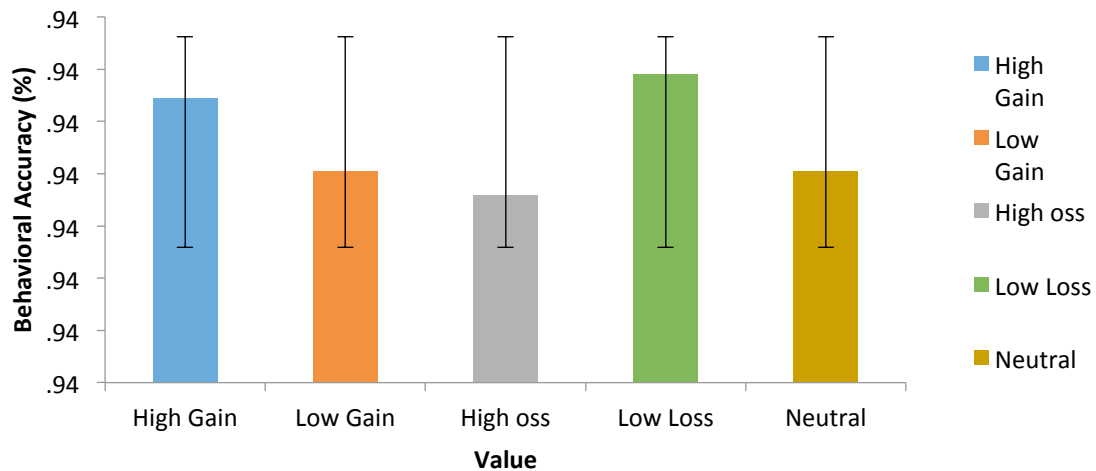
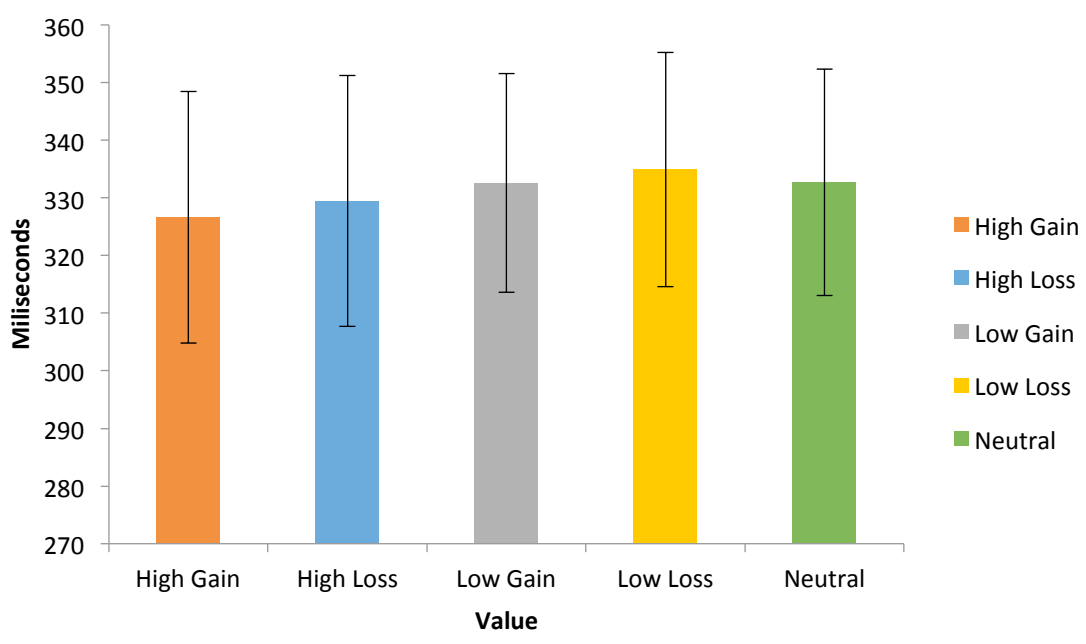Figure A2. *Behavioral accuracy as a function of value with standard deviations as standard error bars (SD +/- 1).*

Appendix B Continued
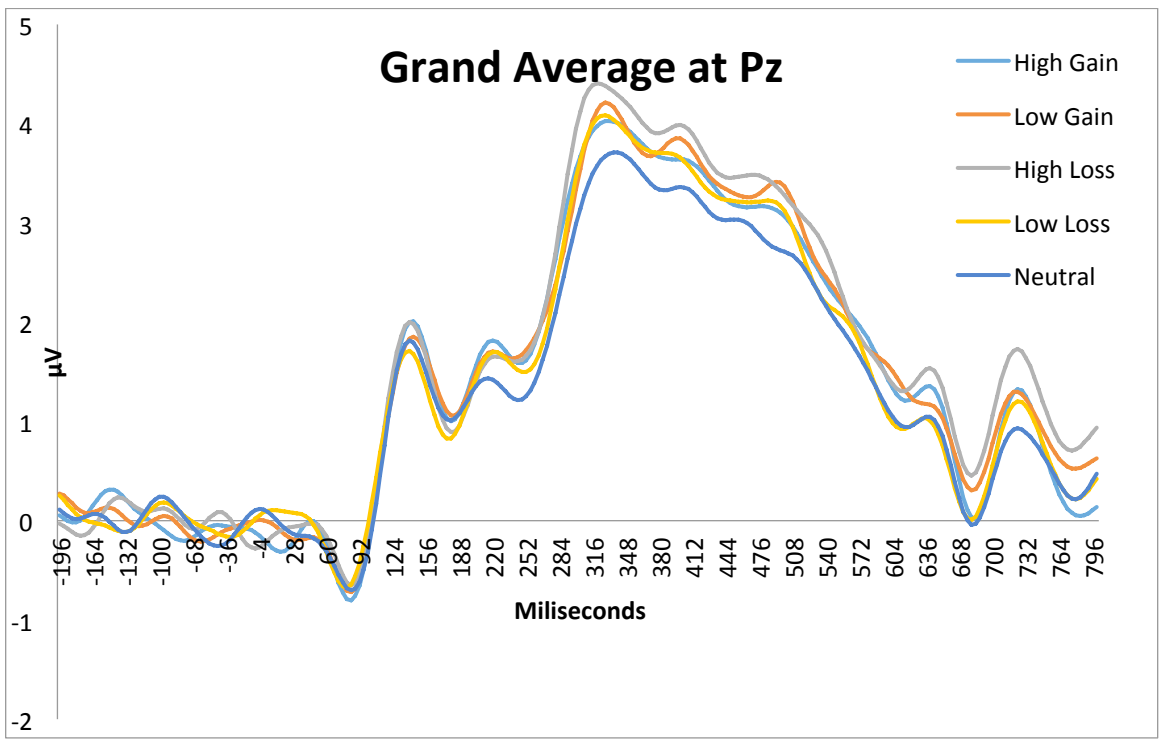
Figure A3. *Grand Average at midline parietal electrode (Pz) from -196 ms to 800 ms.*
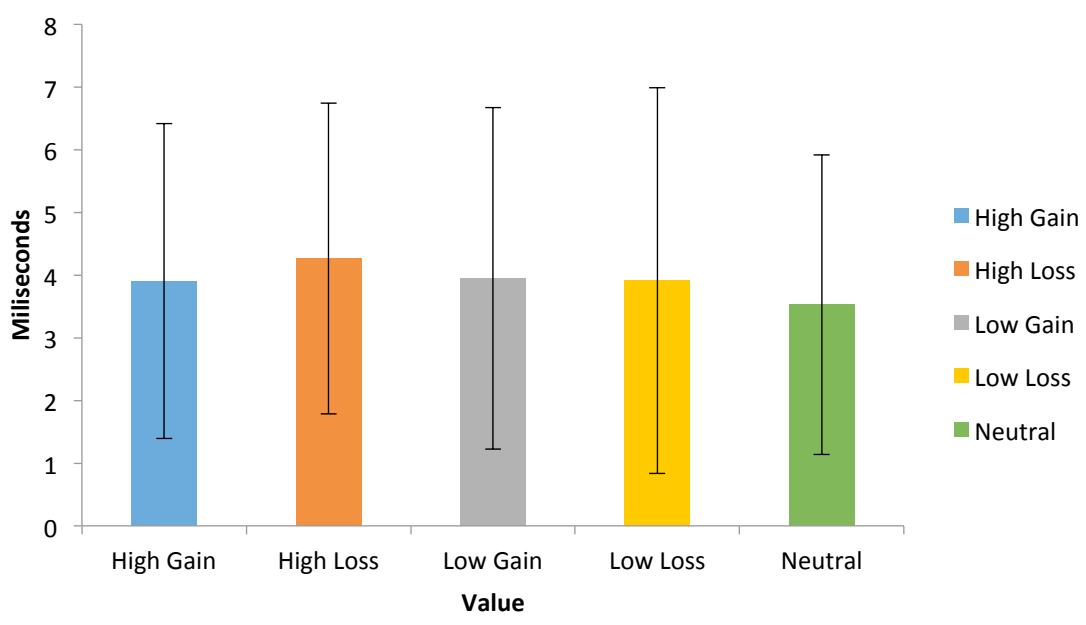
Figure A4. *Mean P3 amplitude as a function of value with standard deviations as standard error bars (SD +/- 1).*

Appendix B Continued
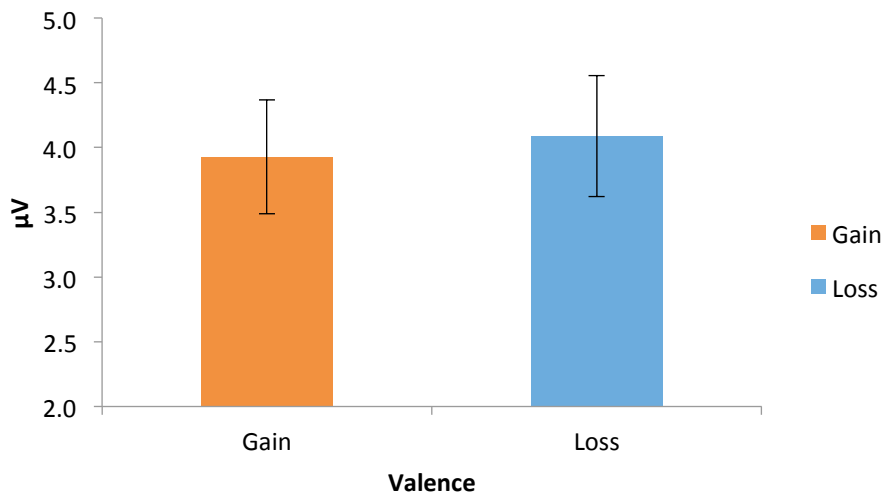
Figure A5. *Mean P3 amplitude as a function of valence with standard error bars.*
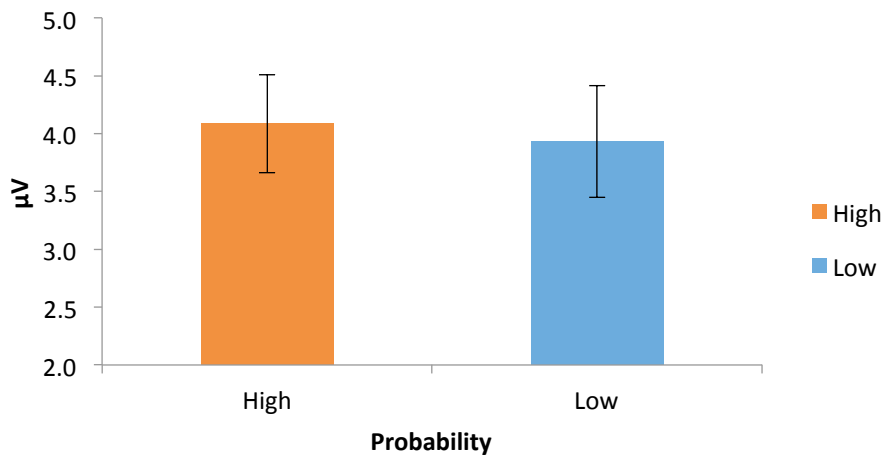
Figure A6. *Mean P3 amplitude as a function of probability with error bars.*

Appendix B Continued
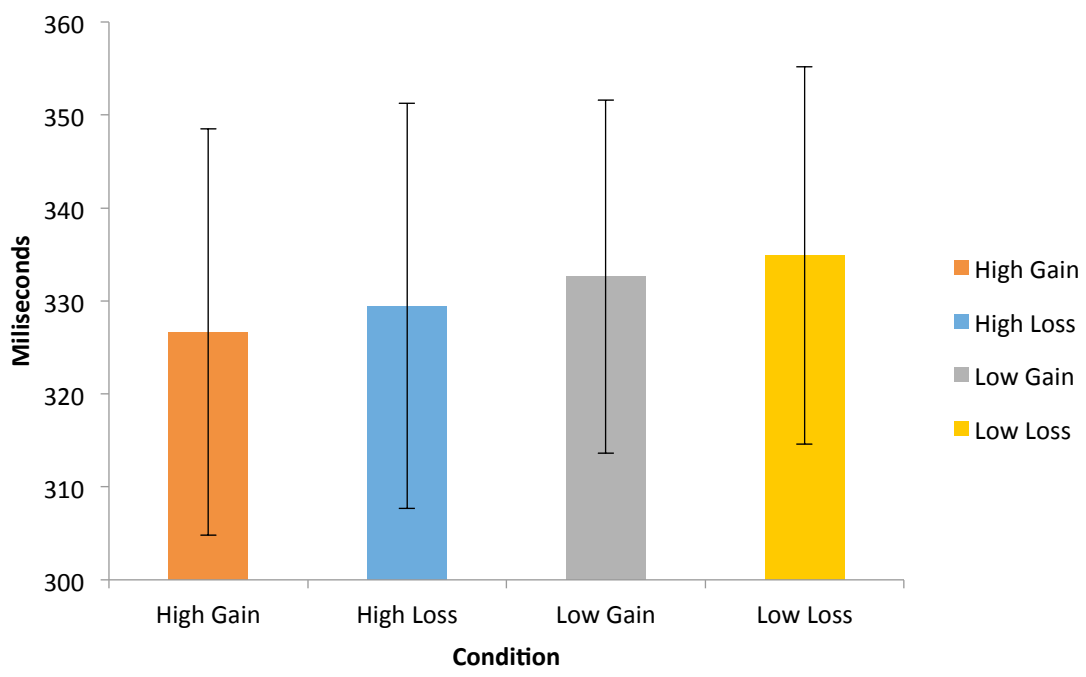
Figure A7. *Mean P3 amplitude as a function of probability and valence with standard deviations as error bars (SD +/- 1).*

Figure A8. *Mean latency as a function of value with standard deviations as standard error bars (SD +/- 1).*
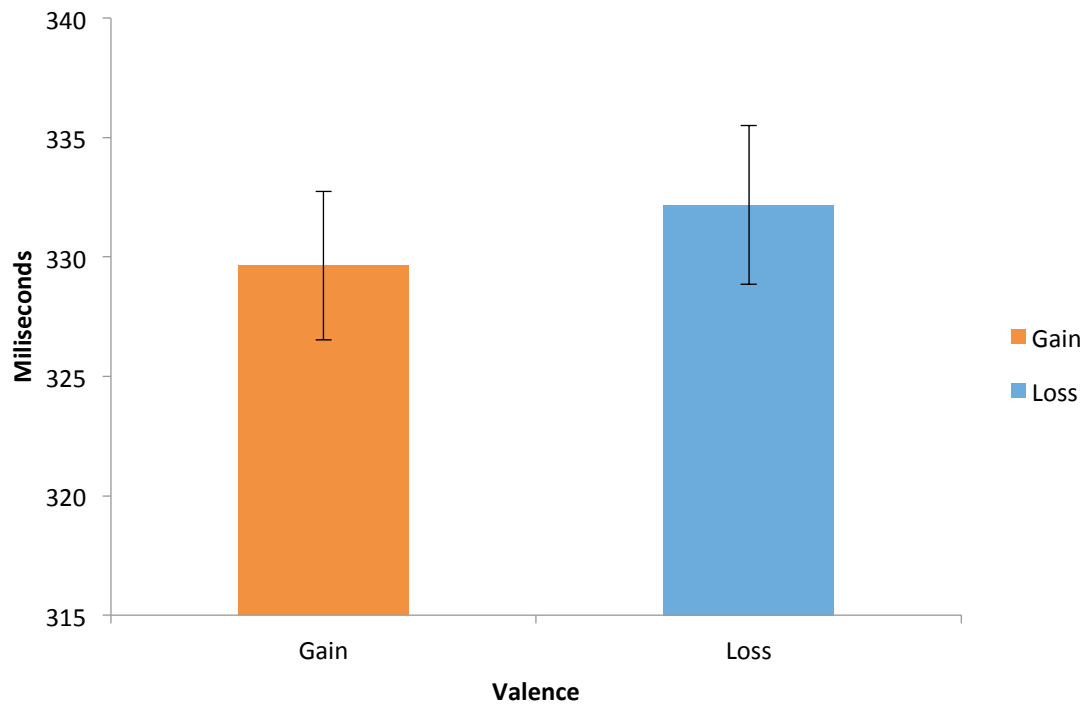
Appendix B Continued

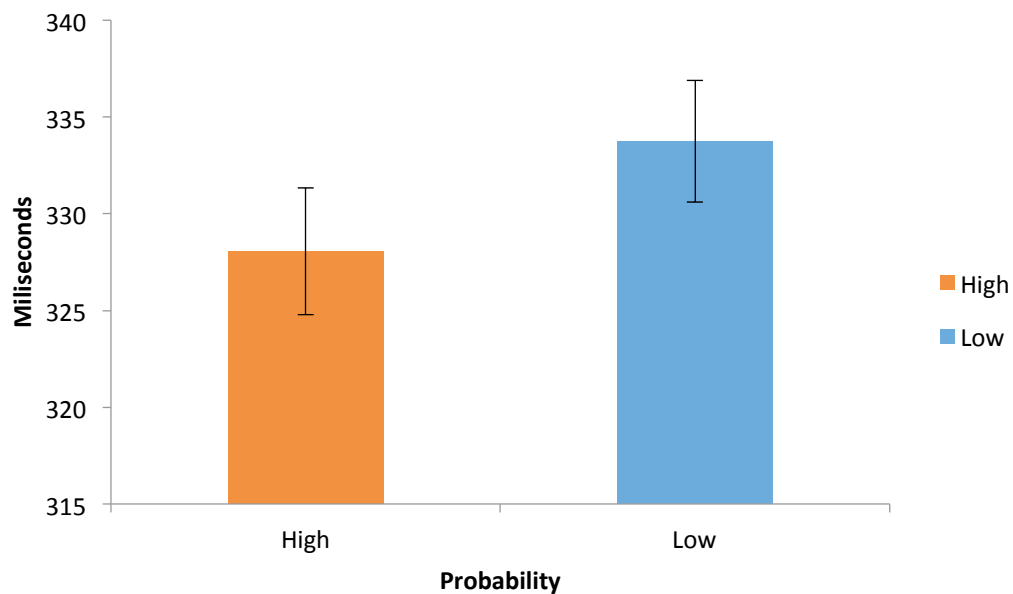Figure A9. *Mean latency as a function of valence with standard deviations as standard error bars (SD +/- 1).*

Figure A10. *Mean latency as a function of probability with standard deviations as standard error bars (SD +/- 1).*
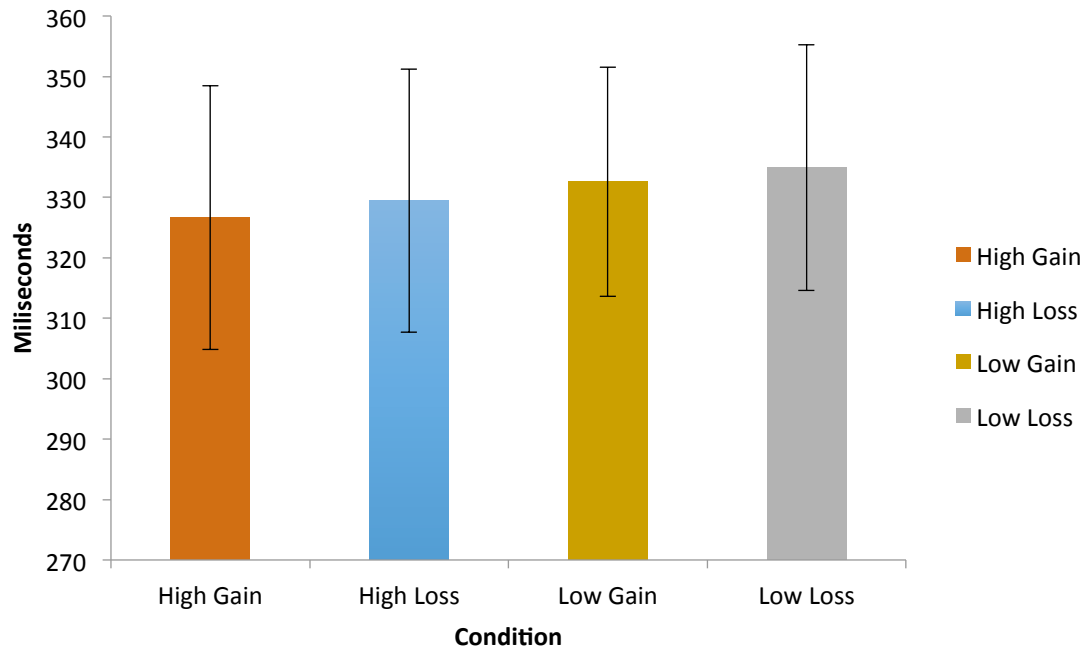
Appendix B Continued

Figure A11. *Mean latency as a function of probability and valence with standard deviations as standard error bars (SD +/- 1).*