

## Using Classification to Understand the Motivation-Learning Interface

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### **I. Introduction**

Most behavior is motivated. As we maneuver through the environment, we are constantly selecting behaviors from a large repertoire of possibilities. Cognition plays a large role in selecting a behavior, but the selected behavior is also strongly determined by our motivational state to approach positive outcomes or avoid negative outcomes. Cognitive research typically focuses on information processing and its effects on learning and behavior with little attention paid to the factors that drive or motivate one to act.

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The influence of active goals on behavior has been the focus of recent social psychological research (e.g., Aarts, Gollwitzer, & Hassin, 2004; Ferguson & Bargh, 2004; Fishbach, Friedman, & Kruglanski, 2003; Higgins, 2000), but little work has examined the effects of motivation on learning (cf. Maddox, Baldwin, & Markman, in press; Markman, Baldwin, & Maddox, in press; Markman, Maddox, & Baldwin, in press). A complete understanding of the relationship between learning and behavior requires a focus on the interplay between motivation and cognition (Carver & Scheier, 1998; Higgins, 1997).

The broad aim of this chapter is to generate a renewed interest in bridging the artificial gap that has formed between research focused on motivation and research focused on learning. The two were intimately related in the 1950's and 1960's (Miller, 1957, 1959; Young, 1959), but since then they have diverged, partially because psychology became more divided and area-driven. Work on learning became the domain of cognitive and animal psychologists, whereas motivation was studied by social and educational psychologists. Furthermore, research in cognitive psychology has often focused on the characteristics of particular tasks (such as classification, or visual search), and so there has been little emphasis on integrating phenomena across domains.

There has been a parallel development in cognitive psychology and neuroscience. Cognitive psychology has begun to generate more integrative theories. At the same time, research in neuroscience makes clear that the brain does not distinguish between motivational areas and learning areas. In fact, some of the most important brain regions for learning such as the prefrontal cortex, the anterior cingulate and the caudate nucleus are either directly or indirectly interconnected with brain regions known to be involved in motivation, affect, and personality, such as the amygdala and the orbitofrontal cortex just to name two. In addition, detailed neurobiological theories are beginning to take hold that postulate specific interdependencies between “cognitive” and “motivational/emotional/personality” brain regions (e.g., Ashby, Isen & Turken, 1999; Bechara, Damasio, & Damasio, 2000; Gray, 1987; Pickering & Gray, 2001). Although the bulk of the theoretical development in this chapter will be behaviorally-based, we will explore the neurobiological underpinnings in some detail in section VIII.

The more specific aim of this chapter is to provide a framework for exploring motivational influences on learning. Specifically, we examine the influence of regulatory focus (Higgins, 2000) on perceptual classification learning. Perceptual classification learning provides an excellent domain for studying the motivation-learning interface, because quick and accurate classification is central to the survival of all organisms and is performed thousands of times a day. In addition, a number of sophisticated mathematical models have been developed that provide the researcher with insight into the strategies that people adopt throughout learning.

In the next (second) section we briefly review Regulatory Focus Theory (Higgins, 2000), and develop a framework for investigating the influence of motivation on behavior. The framework identifies a number of key personality, motivational, and environmental factors that interact to determine performance on learning tasks. The third section applies this framework to classification learning, and outlines two strong predictions that can be generated from the framework. The fourth section reviews recently published studies from our laboratory and several ongoing studies that provide initial tests of these predictions. The fifth section extends the framework to the domain of decision criterion learning. We conclude with some general remarks.

## **II. A Framework for Examining the Motivation-Classification Learning Interface**

The motivation literature makes a distinction between approach and avoidance goals (e.g., Carver & Scheier, 1998; Lewin, 1935; Markman & Brendl, 2000, Miller, 1959). Goals with positive states that one wishes to achieve are called approach goals, whereas goals with negative states that one wishes to avoid are called avoidance goals. Higgins (1987, 1997) proposed regulatory focus theory that extends this idea of approach and avoidance by suggesting that, orthogonal to approach and

avoidance goals, there may be psychological states of readiness or sensitivity for potential gains/non gains or losses/non losses that tune the sensitivity of the motivational system. Specifically, a promotion focus activates an approach mode of processing that focuses the motivational system on the presence or absence of gains in the environment, whereas a prevention focus activates an avoidance mode of processing that focuses the motivational system on the presence or absence of losses in the environment.

Higgins and colleagues (Higgins, 1987, 1997; Higgins, Roney, Crowe, & Hymes, 1994) outline three aspects of regulatory focus. First, people differ in their chronic focus (also referred to as person focus). Chronic focus is an a priori predisposition toward a promotion or a prevention focus. Higgins (1987) suggested that a promotion focus is associated with a person's desire to achieve ideal states, which are defined as that person's hopes, desires, or aspirations. In contrast, a prevention focus is associated with a person's desire to achieve ought states, which are defined as that person's duties obligations, or responsibilities.<sup>21</sup> The strength of a person's predisposed focus toward an ideal or ought state can be measured in a number of ways. One that is popular is to have each person provide a list of attributes that describe how they ideally would like to be. For each attribute the person rates the extent to which they ideally would like to have that attribute and the extent to which they actually possess the attribute. A similar procedure is followed for attributes that describe how they ought to be. Large discrepancies between a person's ideal attributes and their beliefs about their actual attributes are associated with a promotion focus. Large discrepancies between a person's ought attributes and their beliefs about their actual attributes are associated with a chronic prevention focus (see e.g., Shah et al, 1998 for details). The essential idea is that these discrepancies reflect the degree to which people believe traits for ideal (i.e., approach) and ought (i.e., avoidance) states that are accessible for that individual are also part of their self concept. To the extent that there are significant discrepancies, they likely reflect unfulfilled goals of the individual and consequently will help to determine chronic focus.

A second key aspect of regulatory focus is a person's situational focus (also referred to as incentive focus), which is induced by aspects of the current situation. If someone is pursuing a potential gain, then they can be placed in a state of readiness for gain and nongain situations in general. Likewise, if someone is attempting to avoid a loss, they can be placed in a state of readiness for loss and nonloss situations in general.

Unlike chronic focus which is an attribute of a person, situational focus can be manipulated experimentally. Situational focus manipulations are relatively easy to instantiate. As one example, Crowe and Higgins (1997; see also Markman, Kim, & Brendl, 2005) told all participants that they would complete a recognition memory task followed by a second task. The promotion participants were told that if they did well on the recognition task, the second task would be one that they "liked", whereas prevention participants were told that if they did not do well on the recognition task the second task would be one that they "disliked" (liked and disliked tasks were determined separately for each participant based on pre-testing). As a second example, Shah, Higgins, and Friedman (1998) had participants solve anagrams. The promotion participants were paid a base salary of \$4 but were told that they could earn an extra \$1 if they found 90% of the anagram solutions. Prevention participants were paid a base salary of \$5 but were told that they would lose \$1 if they missed more than 10% of the anagram solutions.

A third key aspect of regulatory focus is the idea of *regulatory fit* (Avnet & Higgins, 2003; Higgins, 2000; Higgins, Chen Idson, Freitas, Spiegel, & Molden, 2003; Lee & Aaker, 2004; Shah et al, 1998). This term has been used in a few different ways in the literature, and so it is worth unpacking them a bit.

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<sup>2</sup> Higgins (1997) suggests that a person's predisposition toward ideal end states and a chronic promotion focus versus ought end states and a chronic prevention focus is related to the environment in which they were raised. Children raised in a nurturant environment are more likely to have a chronic promotion focus whereas children raised in a more security minded environment are more likely to have a chronic prevention focus.

First, there is a potential fit between chronic and situational focus. That is, a person may have a chronic promotion focus (because of a large ideal-actual discrepancy) or a chronic prevention focus (because of a large ought-actual discrepancy). Individuals are likely to exhibit better performance in a cognitive task when there is a fit between their chronic focus and the situational focus induced by a task than when there is a mismatch between these foci. For example, in Study 1 from Shah et al (1998), each participant completed two experimental sessions with a minimum of 3 weeks between sessions. In session 1 chronic focus (i.e., ideal and ought strength) was measured. In session 2 each participant was asked to complete 10 anagrams under a situational promotion or prevention focus. The regulatory fit prediction was that people with a chronic promotion focus should perform better than people with a chronic prevention focus under a promotion situational focus, whereas people with a chronic prevention focus should perform better than people with a chronic promotion focus under a prevention situational focus. The results from Study 1 supported the predicted interaction.

A second type of regulatory fit focuses on the relationship between a person's current regulatory focus and the reward structure of the task (also referred to as goal attainment means; Crowe & Higgins, 1997; Higgins, Roney, Crowe, & Hymes, 1994; Shah, et al, 1998). Many tasks can be accomplished by multiple means. For example, in many learning experiments, people may receive points for some responses and lose points for others. One might try to maximize the number of points obtained by focusing on gaining points or alternatively by focusing on avoiding the loss of points. Situations in which one can gain points involve a gain/nongain reward structure. Situations in which one can lose points involve a loss/nonloss reward structure.

There is some reason to believe that people also perform better when there is a fit between the person's current regulatory fit and this reward structure. As one demonstration of this point, Shah et al. (1998) hypothesized a three way interaction between chronic focus, situational focus, and the reward structure of the task. As outlined earlier, they predicted better anagram performance when chronic and situational focus matched than when they mismatched. They also predicted that the nature of the match—chronic promotion with situational promotion versus chronic prevention with situational prevention—would affect which means were used for goal attainment. Specifically, chronic promotion focus participants given a promotion situational focus should pursue gaining points more than losing points, and chronic prevention focus participants given a prevention situational focus should pursue avoiding losing points more than gaining points. Their Study 2 provided a test of this hypothesis. Session 1 measured chronic focus in the same way as in Study 1. In session 2, participants were asked to solve 6 “red” and 6 “green” anagrams and that the goal was to finish with at least 4 points. Participants were told that for each green anagram they would earn 1 point if they found all of the words. Participants were also told that for each red anagram they would lose 1 point if they did not find all of the words. The promotion situational focus participants were told that they would earn \$4 but if they gained 4 or more points they would earn an extra \$1. The prevention situational focus participants were told that they would earn \$5 but if they failed to gain 4 or more points they would lose \$1. As predicted, chronic promotion focus participants given a promotion situational focus pursued the green anagrams (the gains reward structure) more than the red (the losses reward structure), whereas chronic prevention focus participants given a prevention situational focus pursued the red anagrams more than the green.

For completeness, there is a third form of regulatory fit that involves value. In particular, people's judgment of the worth of objects is influenced by the fit between the processes by which they evaluate an object and their regulatory focus. As one example, Higgins, Idson, Freitas, Spiegel, and Molden (2003) had people with a promotion or prevention focus evaluate items for what they would gain by obtaining the object or what they would lose by giving up the other object. Promotion focused subjects valued objects more when they focused on what was to be gained by owning it than by what they would give up by not owning it. In contrast, prevention-focused subjects showed the reverse pattern, valuing objects more when they focused on what they would give up than on what they would gain.

The interaction between chronic focus, situational focus, and the reward structure of the task has been studied extensively in the literature (Higgins & Spiegel, 2004). Subsets of these motivational factors have been found to affect performance in a number of tasks including problem solving (anagrams; Shah et al, 1998), decision making (recognition memory; Crowe & Higgins, 1997), and consumer behavior (Lee & Aaker, 2004; Markman, Kim, & Brendl, 2005). This work has significantly advanced our understanding of the motivation-cognition interface. In the next section we apply this motivational framework to classification learning. To anticipate, we begin by examining the potential neurobiological underpinnings of regulatory focus theory and its interaction with classification learning. We also extend the notion of regulatory fit to explore the relationship between the processes engendered by a particular regulatory focus and the type of task being performed.

### **III. Applying the Regulatory Fit Framework to Classification**

In this section we apply the regulatory fit framework outlined above to the task of perceptual classification learning. Because our interests lie primarily with drawing cause-effect inferences, we restrict our attention to manipulations of situational focus and the reward structure of the task. To be clear we are not discounting the importance of chronic regulatory focus nor its interaction with the other forms of regulatory focus. On the contrary, an understanding of how chronic predispositions affect learning is critical to a complete understanding of the motivation-cognition interface. Even so, our work is experimental and thus a narrower focus is required.

Classification learning encompasses a huge literature (see Wisniewski, 2002 for a review) that includes semantic categories, natural categories, and artificial perceptual categories, to name a few. Because our interest is in learning, we take the approach of constructing novel, artificial categories from collections of perceptual dimensions. This approach allows us to examine the processes involved in classification learning, and to examine a wide range of category structures under controlled experimental conditions. This approach allows us to define rigorously the optimal classifier (a hypothetical device that maximizes long-run reward) and to compare human performance with that of the optimal classifier. In the next sub-sections we review briefly the growing literature on the neurobiological underpinnings of perceptual classification learning, and loosely tie these to the notion of regulatory fit.

#### **A. Neurobiological Underpinnings of Perceptual Category Learning**

Classification learning involves laying down a memory trace that improves the efficiency (i.e., accuracy and speed) of responding. It is now widely accepted that mammals have multiple memory systems (Poldrack & Packard, 2003; Schacter, 1987; Squire, 1992), and there is a growing consensus that multiple classification learning systems exist. Starting in the 1980's a mounting body of research suggested that participants have available multiple processing modes that can be used during classification. Well established in the literature is a distinction between classification based on a rule versus classification based on overall similarity (Allen & Brooks, 1991; Erickson & Kruschke, 1998; Folstein & Van Petten, 2004; Kehler-Nelson, 1984; Nosofsky, Palmeri, & McKinley, 1994; Reheger & Brooks, 1993; Smith & Shapiro, 1989). Rule-based classification is accomplished when an individual forms an explicit verbal rule that distinguishes between members of different categories. Similarity-based classification involves classifying a new stimulus based on some function of the similarity between the new instance and a stored category representation.

Much evidence supports the claim that there are multiple classification learning systems and that they involve unique (though overlapping) neural systems. This empirical support comes from a wide range of research areas including animal learning (McDonald & White, 1993, 1994; Packard & McGaugh, 1992), neuropsychology (Filoteo, Maddox, & Davis, 2001a, 2001b; Maddox & Filoteo, 2001, in press; Myers, Shohamy, Gluck, Grossman, Onlaor, & Kapur, 2003), functional neuroimaging (Filoteo, et al, in press; Poldrack, Prabhakaran, et al., 1999, Reber, Stark, & Squire, 1998; Seger & Cincotta, 2002, 2005; Smith, Patalano, & Jonides, 1998), and cognitive psychology (for reviews, see Keri, 2003; and Maddox & Ashby, 2004).

One of the most successful multiple systems models of classification learning, and the only one that specifies the underlying neurobiology, is the COmpetition between Verbal and Implicit Systems model (COVIS; Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & Waldron, 1999). COVIS postulates two systems that compete throughout learning – an explicit, hypothesis-testing system and an implicit, procedural-based learning system. COVIS assumes that, in humans, the two systems mediate the learning of different types of category structures<sup>32</sup>. Briefly, COVIS assumes that rule-based category learning is dominated by the explicit hypothesis-testing system that uses working memory and executive attention and is mediated by a circuit that includes the anterior cingulate, the prefrontal cortex, and the head of the caudate nucleus. Frequently, the rule that maximizes accuracy (i.e., the optimal rule) is easy to describe verbally. For example, Figure 1a presents a scatterplot of stimuli from a rule-based condition with four categories. Each point in the plot denotes the length and orientation of a single line stimulus (see Figure 1c for an example) with different symbols denoting different categories. In this example, the rule is to give one response to short, shallow angle lines, a second response to short, steep angle lines, a third response to long, shallow angle lines, and a fourth response to long, steep angle lines. To solve this task, the explicit hypothesis-testing system learns the criterion between “short” and “long” and between “shallow” and “steep”, and learns the mapping between short/long and shallow/steep lines and the four category labels.

-----Figure 1-----

In contrast, information-integration category learning is dominated by the implicit procedural-based learning system that depends on a reward signal to strengthen the appropriate (stimulus-category) associations in a relatively automatic fashion (Ashby et al., 1998; Ashby & Ell, 2001). This system is mediated largely within the tail of the caudate nucleus (with visual stimuli) and learning relies heavily on a dopamine mediated reward signal<sup>43</sup>. Figure 1b presents a scatterplot of stimuli from an information-integration condition with four categories. Notice that the information-integration category structure can be derived from the rule-based category structure by rotating the location of each stimulus counter-clockwise 45 degrees in the length-orientation space. Unlike the decision rule in the rule-based condition, the resulting information-integration classification rule is nonverbalizable.

This represents only a cursory review of COVIS and the proposed underlying neurobiology. A more detailed discussion can be found in Ashby and Valentin (in press). For the present purposes, what is most important to note is that the hypothesis-testing system relies heavily on frontal brain regions, whereas the procedural-based learning system relies heavily on sub-cortical regions such as the tail of the caudate nucleus.

### **B. Neurobiological Underpinnings of Regulatory Focus**

As reviewed above, regulatory fit leads participants to generate more alternatives in an anagram task (Crowe & Higgins, 1997; Shah et al, 1998). Solving anagrams requires the participant to select and test numerous alternatives. This process of selecting and testing alternatives can be defined generally as cognitive flexibility. The anterior cingulate, a frontal brain structure utilized by the hypothesis-testing system, is thought to be critically involved in the selection of alternatives and has been linked directly to cognitive flexibility (Posner & Petersen, 1990). In the next sections that

<sup>3</sup> It is important to note that we are not arguing that these are the only two classification learning systems. On the contrary, there is good evidence that at least two additional systems: an episodic-memory driven and a perceptual-priming system likely exist. The interested reader is directed to Ashby and Maddox (2005) or Keri (2003) for a review.

<sup>4</sup> In primates, all of extrastriate visual cortex projects directly to the tail of the caudate nucleus, with about 10,000 visual cortical synapses converging onto each medium spiny cell in the caudate (Wilson, 1995). These medium spiny cells then project to prefrontal and premotor cortex (via the globus pallidus and thalamus; e.g., Alexander, DeLong, & Strick, 1986). The idea is that an unexpected reward causes substantia nigra neurons to release dopamine from their terminals in the caudate nucleus (Hollerman & Schultz, 1998; Schultz, 1992), and that the presence of this dopamine strengthens recently active synapses (Arbuthnott, Ingham, & Wickens, 2000).

develop and test our proposed motivation-learning framework, we will not elaborate on the possible neurobiological underpinnings, but rather leave a more detailed discussion for the Summary and Future Directions section. For now suffice it to say that we assume that cognitive flexibility is at least partially mediated by the anterior cingulate.

### C. Classification Learning Predictions

Our working hypothesis is that regulatory fit; specifically, a fit between situational focus and the reward structure of the task, leads to greater cognitive flexibility. Taken a step further, we suggest that cognitive flexibility can be loosely associated with frontal brain areas, in particular the anterior cingulate.

The complete set of hypotheses from this view are summarized in Table 1. We can state our predictions in two parts. First,

Prediction 1: Regulatory fit manipulations should lead to better rule-based classification learning when cognitive flexibility is advantageous for solving the task, but should lead to worse rule-based classification learning when cognitive flexibility is not advantageous.

-----Table 1-----

We define cognitive flexibility as an increase in one's ability or willingness to try different strategies across trials to achieve some stated goal, as opposed to sticking with a single strategy and making small incremental changes during learning. If the task is one for which a simple, highly salient strategy will achieve the participant's goal or one in which the necessary rule is obvious from the start, then the increase in willingness to try more complex rules associated with cognitive flexibility may not be acted upon. In contrast, if the task is one for which a complex, low salience strategy is necessary to achieve the participant's goal or the rule is not obvious initially then increased cognitive flexibility should be advantageous.

Prediction 2: Regulatory fit manipulations should affect the hypothesis-testing classification system, but not the procedural-based learning classification system. By extension, regulatory fit manipulations should affect rule-based classification learning more than information-integration category learning.

Prediction 2 follows because regulatory fit is assumed to lead to greater cognitive flexibility. Cognitive flexibility is associated with greater activity in the anterior cingulate which is a critical brain structure in the hypothesis-testing but not the procedural-based classification learning system. Because rule-based classification learning is dominated by the hypothesis-testing system, and information-integration classification learning is dominated by the procedural-based learning system, regulatory fit effects should be strongest for rule-based classification learning. Prediction 2 is more tenuous for reasons that will be discussed later.

The studies we have conducted over the past few years have addressed some of the predictions summarized in Table 1. In the following sections, we review this work. One series of studies examines the effects of regulatory fit on rule-based classification learning. In some cases cognitive flexibility is advantageous for solving the task, whereas in others cognitive flexibility is not advantageous for solving the task. We then turn to a study that examines the effects of regulatory fit on information-integration category learning.

## IV. Regulatory Fit Effects on Rule-Based Classification Learning

### A. Cognitive Flexibility Is Advantageous

#### 1. Maddox et al (in press), Experiment 1 (Gains Reward Structure)

The first study we discuss explored a condition in which people learned rule-based categories. We designed the categories so that flexibility in the selection of a classification strategy would be advantageous. The task used a Gains reward structure. This setting is summarized in the first row of Table 1. From this table, we would expect that subjects given a situational promotion focus would perform better than would subjects given a situational prevention focus.

To create a setting in which cognitive flexibility was useful, the task was designed so that a simple highly-salient uni-dimensional rule yielded reasonable performance, but a more complex less-

salient conjunctive rule yielded higher performance that allowed the participant to exceed a performance criterion. Importantly, correct responses were rewarded with a gain in points on each trial, whereas errors led to no gain in points. Thus, there was a match between situational focus and the reward structure of the task for situational promotion focus participants, but there was a mismatch for situational prevention focus participants.

The stimulus on each trial was a line whose length, orientation, and horizontal position on the computer screen varied across trials. A scatter-plot of the stimuli in three-dimensions along with the optimal decision criteria on length and orientation is displayed in Figure 2a. The optimal decision rule was conjunctive and required the participant to set a criterion on length and a criterion on orientation and to use the rule: Respond A if the length is long and the orientation is steep; otherwise respond B. A participant using the optimal length and orientation decision criteria could attain 100% accuracy, whereas the most accurate uni-dimensional rules on length, and orientation yielded 83% accuracy. The position dimension was irrelevant to solving the task (i.e., the optimal rule did not involve position) but was constructed in such a way that a uni-dimensional rule on position also yielded 83% correct. The position dimension was included because pilot studies conducted in our lab suggest that it is highly salient and thus we expected participants to focus initially on this dimension. To summarize, a participant could perform quite well while focusing on only one stimulus dimension such as position, but a conjunction of the length and orientation dimension information was required to achieve performance that exceeded the bonus criterion. Each participant completed several blocks of trials in the experiment.

-----Figure 2-----

Participants in the situational promotion focus condition were told that they could earn an entry into a drawing for \$50 if they exceeded a performance criterion during the final block of trials (equivalent to meeting or exceeding 90% accuracy). Participants in the situational prevention focus condition were given an entry into the drawing for \$50 upon entry into the laboratory, but were told that they had to exceed the same performance criterion in order to keep the entry. Notice that any participant using a uni-dimensional rule will not exceed the performance criterion. Instead, the participant must abandon the simple uni-dimensional rule (either on length, orientation or position) in favor of the more complex conjunctive rule to exceed the performance criterion. Because discovery of the optimal conjunctive rule requires greater cognitive flexibility (i.e., a willingness to abandon the reasonably accurate, simple uni-dimensional rule in favor of the more complex conjunctive rule required to exceed the performance criterion), we predicted that participants given a situational promotion focus will discover the rule sooner, and thus will learn more quickly than participants given a situational prevention focus.

At the beginning of each block a “point meter” was set to zero. The criterion was shown as a line across the meter, and was labeled “Bonus.” At the end of each block of trials the participants were given feedback on their performance in that block. If they exceeded the bonus criterion in the situational promotion condition they were told “If that had been the last block of trials you would have earned an entry into the drawing for \$50.” If they exceeded the bonus criterion in the situational prevention condition they were told “If that had been the last block of trials you would have kept you entry into the drawing for \$50.” If it was the final block they were told whether they gained or kept their entry into the drawing.

Three sets of analyses were conducted on the accuracy data. First, we identified the first block of trials for which each participant met or exceeded the 90% performance criterion. This denotes the first block of trials for which the participant would have received feedback that, had that been the final block of trials, they would have earned an entry into the drawing (promotion focus) or they would have kept their entry into the drawing (prevention focus). As predicted, promotion focus participants exceed the performance criterion sooner than did prevention focus participants. Second, for each block of trials we compared the proportion of promotion and prevention focus participants who met or exceeded the 90% performance criterion. As predicted, more promotion focus participants (63.3%)

exceeded the criterion during the final block than did prevention participants (36.7%). Finally, we computed the average accuracy in each block for the promotion and prevention participants. As expected, promotion participants were more accurate (91.3%) than prevention participants (86.5%) during the final block of trials. Taken together the accuracy-based analyses converge in suggesting that participants given a promotion focus (a) exceeded the performance criterion earlier in training, (b) were more likely in general to exceed the performance criterion necessary to earn an entry into the drawing, and (c) obtained higher overall accuracy rates.

The accuracy based analyses support our claim that the regulatory fit between the situational promotion focus and the gains reward structure of the task led to greater cognitive flexibility. Implicit in this hypothesis is the assumption that cognitive flexibility led participants to abandon the highly salient uni-dimensional rule in favor of the more complex, less salient conjunctive rule. To test this hypothesis rigorously we fit a number of decision bound models separately to the block by block data from each participant. The details of the model fitting procedure are outlined in Maddox et al (in press). We fit three models that assumed a uni-dimensional rule based strategy: one that assumed a rule on length, another on orientation, and a third on position. We also fit a sub-optimal conjunctive rule model that estimated the decision criterion values from the data, and the optimal conjunctive rule model that assumed the optimal decision criterion values.

Following the approach taken with the accuracy data, we conducted a number of separate analyses on the modeling results. First, as expected, the proportion of data sets best fit by the uni-dimensional position model was higher for prevention participants than promotion participants. This pattern suggests that prevention focus participants were less likely to abandon this simple rule in favor of the more complex conjunctive rule. Second, we identified the first block of trials for which a conjunctive rule model provided the best account of the data separately for each participant. Promotion participants' data was best fit by a conjunctive model earlier in learning than prevention participants. Finally, the proportion of participants whose data was best fit by a conjunctive rule model was higher for promotion participants than prevention participants.

Taken together these results suggest that a regulatory fit between a situational promotion focus and a gains reward structure leads to greater cognitive flexibility and thus better rule-based classification learning when the task is one that requires cognitive flexibility. Thus, this pattern supports the predictions in the first row of Table 1.

## **2. Pilot Data (Losses Reward Structure)**

Maddox et al (in press), Experiment 1 provides support for our claim that a regulatory fit between the situational focus and the reward structure of the task leads to increased cognitive flexibility and better performance in a task for which a highly salient, simple rule is sub-optimal, and a less salient, complex rule is optimal. Experiment 1 examined only a gains reward structure though.

In a recent pilot study conducted in our lab, we replicated Maddox et al (in press), Experiment 1, but with a losses reward structure. As summarized in the second row of Table 1, our motivation-learning framework predicts that—under these conditions--there will be a regulatory fit between situational prevention focus participants and the reward structure, and a regulatory mismatch between the situational promotion focus participants and the reward structure. Because the category structure is one that requires cognitive flexibility, and because situational prevention participants should be more cognitively flexible (under a losses reward structure), we predicted a pattern opposite of that observed in Maddox et al (in press). Specifically, we predicted (a) faster, more accurate classification learning for situational prevention participants, and (b) an earlier shift away from the use of a uni-dimensional rule on position toward a conjunctive rule on length and orientation.

All aspects of the experiment were identical to those from Maddox et al (in press), Experiment 1 except for the details of the point meter. In this study, participants started out with no points and lost either one point for a correct response or three points for an incorrect response. The zero point on the meter was at the top of the screen, and the bonus line was below that. When the participant made a correct response the point meter went down one point and when they made an incorrect response the

point meter went down three points. Participants earned or kept an entry into the drawing if they kept the point meter above the criterion line, and lost or did not earn an entry if the point meter dropped below the criterion.

We followed the same data analytic procedure for these data as was used in Maddox et al (in press), Experiment 1. Three aspects of the accuracy data were examined. First, as predicted, prevention focus participants exceed the performance criterion sooner than did promotion focus participants. Second, more prevention focus participants exceeded the criterion than did promotion participants. Finally, prevention participants were more accurate overall than promotion participants.

With respect to the model based analyses, three analyses were conducted. First, the proportion of data sets best fit by the uni-dimensional position model was higher overall for promotion focus participants than for prevention focus participants suggesting that promotion focus participants were less likely to abandon this simple rule in favor of the more complex conjunctive rule. Second, prevention participants' data was best fit by a conjunctive model earlier in learning than promotion participants. Finally, the proportion of prevention participants whose data was best fit by a conjunctive rule was larger than that for promotion participants.

### **3. Brief Summary**

The results from Maddox et al (in press), Experiment 1 and the pilot data above provide strong support for our regulatory fit/cognitive flexibility hypothesis. Participants completed a rule-based classification learning task for which a highly salient, simple uni-dimensional rule was sub-optimal and a low salience, complex conjunctive rule was optimal. Importantly, the bonus criterion could be met only if the participant abandoned the simple rule in favor of the more complex rule. Maddox et al (in press) placed participants in a situation for which the reward structure of the task involved gains. Under these conditions, our regulatory fit hypothesis predicts better classification learning for situational promotion focus participants than for situational prevention focus participants. Promotion focus participants, learned faster, reached a higher asymptote, and were found to abandon the simple uni-dimensional rule in favor of the more complex conjunctive rule more quickly. In the pilot study, we placed participants in a situation for which the reward structure of the task involved losses. Under these conditions, our regulatory fit hypothesis predicts better classification learning for situational prevention focus participants than for situational promotion focus participants because the regulatory fit leads to greater cognitive flexibility. Prevention focus participants, learned faster, reached a higher asymptote, and were found to abandon the simple uni-dimensional rule in favor of the more complex conjunctive rule more quickly.

We turn now to a rule-based classification task for which cognitive flexibility should not be advantageous. These conditions are summarized in rows three and four of Table 1. Because cognitive flexibility is not advantageous, and because a regulatory fit between the situational focus and the reward structure of the task is hypothesized to lead to greater cognitive flexibility, we predict worse performance when there is a fit between the situational focus and the reward structure of the task than when there is a regulatory mismatch.

## **B. Cognitive Flexibility Is Not Advantageous**

### **1. Maddox et al (in press), Experiment 2 (Gains Reward Structure)**

Experiment 2 of Maddox et al (in press) examined the effects of regulatory fit on rule-based classification learning when cognitive flexibility was not advantageous for solving the task. We used the same gains reward structure used in Maddox et al (in press), Experiment 1. As summarized in the third row of Table 1, under these conditions, there should be a regulatory fit between the situational promotion focus and the gains reward structure that is predicted to lead to greater cognitive flexibility. Because cognitive flexibility is not advantageous, we predict better performance for the situational prevention focus participants than for the situational promotion focus participants.

We designed a classification task in which conservative changes in a person's criterion would lead to better performance in the task than would large changes that might be associated with high flexibility. As in Maddox et al (in press), Experiment 1 we used a conjunctive rule-based classification

learning task, but instead of a two-category problem where uni-dimensional rules existed that yielded good performance, we used a four-category problem where it was clear early in learning that a two-dimensional rule was required. The stimulus on each trial was a line whose length and orientation varied across trials. Figure 3 displays the category structures. The optimal rule can be described as follows: “Respond A if the length is short and the orientation is shallow; Respond B if the length is short and the orientation is steep; Respond C if the length is long and the orientation is shallow; Respond D if the length is long and the orientation is steep”. Because the two-dimensional nature of the optimal rule is clear early in learning, the type of cognitive flexibility associated with qualitative shifts in the nature of the decision rule will not be useful. Instead, good performance will be achieved through slower, more incremental changes in the decision criterion values. These slower, more incremental changes should be associated with lower levels of cognitive flexibility and thus a prevention focus.

-----Figure 3-----

Two additional characteristics of the task were added to bias the task in favor of low cognitive flexibility. First, the category distributions overlapped requiring the participant to learn a “noisy” criterion between “short” and “long” lines and between “shallow” and “steep” orientations. Second, a base-rate manipulation was introduced. Specifically, categories C and D were presented three times as often as categories A and B. Base-rate manipulations affect the location of the optimal decision criterion and in this study shifted the location of the optimal length criterion away from the equal likelihood criterion (see Maddox, 2002 for details). When the base-rates are unequal, the optimal classifier sacrifices accuracy on the low base-rate categories to increase accuracy on the more prevalent high base-rate categories effectively increasing overall accuracy and long-run reward. The fact that a) the two-dimensional nature of the optimal rule is clear early, b) the location of the optimal criteria are noisy due to category overlap, and c) the base-rate difference shifts the criteria away from the equal likelihood criteria should provide an environment for which low cognitive flexibility is advantageous.

The regulatory fit manipulation is subtle and should not be expected to lead to differential patterns of performance under all conditions. For example, if one constructs a situation in which the “bonus” is easily attainable even with a sub-optimal rule, there should be little effect of regulatory fit because both promotion and prevention focus participants should achieve the goal easily. In contrast, if we create a situation in which the bonus is rarely or never attainable we should observe larger effects of the regulatory fit manipulation. To investigate this possibility, we examined the effects of regulatory fit on four-category conjunctive rule-based classification learning under two “goal states”; one for which the bonus was easily attainable (the attainable goal condition) and one for which the bonus was unattainable (the unattainable goal condition). This resulted in a 2 situational focus x 2 goal state factorial design.

The situational focus manipulation was identical to that from Maddox et al (in press), Experiment 1. Participants in the unattainable goal condition received one point for each correct response and no points for incorrect responses, whereas participants in the attainable goal condition received two points for each correct response and no points for incorrect responses. The bonus criterion was set to 75% of that obtained by the optimal classifier when 2 points could be earned for a correct response. Under these conditions, a participant achieving 100% accuracy in the unattainable goal condition would still not meet the performance criterion. The details of the point meter were identical to those from Maddox et al (in press), Experiment 1.

Several analyses were conducted on the accuracy data. First, because the goal was attainable in the attainable goal conditions we expected that situational promotion and prevention participants would meet or exceed the performance criterion early in learning and at the same rate. As expected both groups achieved the goal early in learning. Second, as predicted, situational focus and attainability interacted in predicting performance. The interaction suggested that (a) situational focus had no effect on performance when the goal was attainable, (b) performance in the prevention-

unattainable condition was high and equivalent to that observed in the two attainable goal conditions, and (c) performance in the promotion-unattainable goal condition was significantly worse than in each of the other three conditions. We predicted worse learning when there was a regulatory fit between the situational focus (promotion) and the reward structure of the task (gains) because this “fit” should lead to greater cognitive flexibility, which is disadvantageous for learning this category structure. We postulated also that this “fit” disadvantage should occur only when there goal is unattainable. Each of these predictions was supported by the accuracy data but it would be useful to determine whether the “fit” effect is truly due to greater cognitive flexibility.

We applied a series of decision bound models to address this issue. The details of the modeling can be found in Maddox et al (in press), but for now suffice it to say that we focus our modeling analyses on a model that assumes that the participant uses a conjunctive rule, but one for which the decision criterion values are estimated from the data. In addition to the two decision criterion parameters (one on length and one on orientation), the model includes a “noise” parameter. In short, the noise parameter provides an estimate of the trial by trial variability in the application of the decision criteria. The noise value should provide a direct test of our cognitive flexibility hypothesis, since greater cognitive flexibility, in the form of larger shifts in the decision criteria, should result in a larger value for the noise parameter. Thus, we predict larger noise estimates in the promotion-unattainable condition than in the other three conditions. In addition, we predict no difference in the noise estimates across these three remaining conditions. As expected, we found no difference in the noise estimates across the two attainable goal and the prevention-unattainable goal conditions, but that there was greater noise variability in the promotion-unattainable goal condition than in any other condition.

## 2. Pilot Data (Losses Reward Structure)

The next step is to replicate Maddox et al (in press), Experiment 2, but with a losses reward structure. As shown in the fourth row of Table 1, under these conditions our motivation-learning framework predicts that there will be a regulatory fit between the situational prevention focus and the reward structure of the task. Because we predict that a regulatory fit will lead to greater cognitive flexibility when the goal is unattainable, we predict worse category learning in the prevention-unattainable goal condition than in the other three conditions, a pattern opposite of what we observed in Maddox et al (in press), Experiment 2. We are currently in the process of running this study.

## C. Rule-Based Classification Learning Summary

Our working hypothesis is that a regulatory fit between the situational focus and the reward structure of the task leads to greater cognitive flexibility. Cognitive flexibility is a frontal-based cognitive process and thus changes in cognitive flexibility should affect learning in classification tasks that involve primarily frontal brain structures. These include rule-based classification learning tasks. In some cases, cognitive flexibility is advantageous for solving the task. Under these conditions, a regulatory fit between the situational focus and the reward structure of the task – that is, a situational promotion focus with a gains reward structure or a situational prevention focus with a losses reward structure – should lead to greater cognitive flexibility and thus better rule-based classification learning. Maddox et al (in press), Experiment 1 and the pilot data presented above support this claim. In other cases, cognitive flexibility is not advantageous for solving the task. Under these conditions, a regulatory fit between the situational focus and the reward structure of the task – that is, a situational promotion focus with a gains reward structure or a situational prevention focus with a losses reward structure – should lead to poor rule-based classification learning because cognitive flexibility is not advantageous. Maddox et al (in press), Experiment 2 supported this claim when the reward structure contains gains. We are currently running a study that tests this hypothesis when the reward structure contains losses. Thus, we have already found empirical support for the predictions in the first three rows of Table 1, and are currently running a study examining the predictions in the fourth row.

## V. Regulatory Fit Effects on Information-Integration Classification Learning

As outlined earlier, we suggest a loose association between regulatory fit and frontal brain structures, such as the anterior cingulate, that support cognitive flexibility. A strong prediction then is that regulatory fit should have little if any effect on information-integration category learning since it is mediated primarily by subcortical structures such as the tail of the caudate nucleus. On the other hand, it is also possible that regulatory fit will have some effect on information-integration category learning through its effects on the hypothesis-testing system.

COVIS assumes that rule-based classification learning is dominated by the hypothesis-testing system, and that information-integration classification learning is dominated by the procedural-based learning system. Even so, COVIS also assumes that these two systems – hypothesis-testing and procedural-based learning – compete on each trial to determine the response of the system. In addition, COVIS assumes that there is a bias toward the output of the hypothesis-testing system early in learning. The idea is that the participant starts by testing out verbalizable rules and only if those fail (e.g., in an information-integration task) will the system begin to shift away from the hypothesis-testing system and toward the procedural-based learning system. Thus, it seems reasonable to suppose that any effects of regulatory fit on information-integration classification learning should be restricted to the early blocks of trials when the hypothesis-testing system is dominant. In addition, the effect could be advantageous or disadvantageous for learning. If increased cognitive flexibility leads the participant to focus more on hypothesis-testing strategies, then cognitive flexibility should adversely affect information-integration classification learning. This weak prediction is summarized in the last two rows of Table 1. This prediction need not be borne out, however. It may be that participants who are high in cognitive flexibility may be more willing to abandon hypothesis-testing strategies in favor of procedural-based learning strategies. At this point, we are taking an exploratory approach toward examining regulatory fit effects on information-integration learning. We assume only that regulatory fit effects should be restricted to the early blocks of trials when the hypothesis-testing system dominates and should disappear later in learning when the procedural-based learning system begins to dominate.

As an initial examination of the effects of regulatory fit on information-integration classification learning, and in an attempt to link this work as closely as possible with our previous work, we conducted a pilot study using the category structures in Figure 2b. Notice that this is very similar to the category structure used in Maddox et al (in press), Experiment 1, in the sense that we included a highly salient uni-dimensional rule on position that achieved reasonable accuracy, but an accuracy rate below that required to earn the raffle entry (situational promotion focus) or to keep the raffle entry (situational prevention focus). The best fitting unidimensional rule on length and on orientation also yielded good performance, but performance below the bonus criterion. To exceed the performance criterion the participant had to focus exclusively on length and orientation and apply an information-integration strategy. In addition, we examine only the gains reward structure. The experimental procedure was identical to that from Maddox et al (in press), Experiment 1.

To date, we have found little if any difference in the proportion of promotion and prevention participants reaching the criterion, although there is a small advantage for the prevention participants early in learning. In addition, the block by block accuracy rates are approximately equal. To more fully examine classification learning strategies, we fit a series of hypothesis testing and information-integration models to the data. Interestingly, a large advantage emerged early in learning for the prevention participants, with over 80% of the participant's data best fit by an information-integration model by the third block of trials. Although speculative, these data suggest that the increased cognitive flexibility for the situational promotion participants under this gains reward structure led them to apply hypothesis-testing strategies for longer than participants with a regulatory mismatch (i.e., the situational prevention participants). The fact that the strategy differences were not born out in the accuracy data are curious, but not unfounded. It is often the case that qualitatively different strategies such as hypothesis-testing and procedural-based learning can yield equivalent performance. The fact

that a performance difference emerges in the models but not in the accuracy data attests to the importance of including model based analyses in these studies.

These pilot data are suggestive and provide initial support for the notion that a regulatory fit – that is, a situational promotion focus under a gains reward structure -- leads to greater cognitive flexibility in information-integration tasks. Cognitive flexibility in this case leads the participant to abandon hypothesis-testing strategies later in the session than participants with a regulatory mismatch. Future work needs to address the situation in which there is a regulatory fit between a situational prevention focus and a losses reward structure. The tentative prediction (outlined in the final row of Table 1) is that a regulatory fit between a situational prevention focus and a losses reward structure should lead to greater cognitive flexibility that leads the participant to abandon hypothesis-testing strategies later in the session than participants with a regulatory mismatch.

## **VI. Summary of Classification Learning Results**

In the previous sections we reviewed work that examined the effects of regulatory fit on rule-based and information-integration classification learning. We tested the hypothesis that a regulatory fit between the situational focus and the reward structure of the task will lead to greater cognitive flexibility. When the task is one for which cognitive flexibility is advantageous, we see better rule-based classification learning for participants in the regulatory fit conditions. When the task is one for which cognitive flexibility is not advantageous, we see better rule-based classification learning for participants in the regulatory mismatch conditions. The results for information-integration classification learning are less clear. At the level of global block by block accuracy there appear to be no effects of regulatory fit between a situational promotion focus and a gains reward structure. On the other hand, the model based analyses suggest that regulatory fit participants use hypothesis-testing strategies longer than regulatory mismatch participants. Clearly more work is needed.

## **VII. Regulatory Fit Effects on Decision Criterion Learning**

In this section we apply our motivation-learning framework to the task of decision criterion learning. We continue to examine the notion of regulatory fit between situational focus and the reward structure of the task, but we examine cases in which the reward structure of the task is biased toward one category over the other. This allows us to examine a different form of cognitive flexibility.

In all of the studies outlined above, the participant's task was to maximize reward (either by maximizing points earned or minimizing points lost). In every case this was equivalent to maximizing accuracy. In other words, the optimal decision rule simultaneously maximized accuracy and reward. This follows because the payoff matrices were unbiased in the sense that the payoff for being correct was identical across categories, and the payoff for being incorrect was identical across categories.

In the real world it is often the case that the payoff matrices are biased. For example, the reward is greater for correctly diagnosing a patient who exhibits chest pain as having a heart attack, than it is to correctly diagnose indigestion. Similarly, the cost of incorrectly diagnosing indigestion in a patient who is having a heart attack could be fatal whereas incorrectly diagnosing a heart attack in a patient who is suffering only from indigestion is not life threatening. A critical aspect of learning under these biased payoff situations is that reward maximization requires the participant to sacrifice some measure of long run accuracy. In other words, the decision rule that maximizes long run accuracy is different from the decision rule that maximizes long run reward. Across a number of studies reviewed by Maddox (2002), we have shown that participants often exhibit a bias toward accuracy maximization even though the strategy that maximizes accuracy leads to sub-optimal reward maximization.

In one study, Markman, Baldwin and Maddox (in press) examined the effects of regulatory fit on performance in a decision criterion learning task for which the payoff structure was biased toward one category and away from the other. In the gains condition, the participant gained more points for being correct than incorrect, and more points for being correct on category A than for being correct on category B. In the losses condition, the participant lost fewer points for being correct than incorrect, and lost fewer points for being correct on category A than for being correct on category B. The gains

and losses conditions reflect the reward structure of the task. Situational focus was manipulated in a manner similar to that outlined above. Situational promotion participants were told that they could earn an entry into a drawing for \$50 if they exceeded a performance criterion, and situational prevention participants were given the entry upon entering the lab but were told that they had to exceed a performance criterion to keep the entry.

The stimulus on each trial was a bar that varied across trials in height. Category overlap was large ( $d' = 1.0$ ) making the task difficult. The category structure is depicted in Figure 4a. Situational focus was manipulated across participants whereas the reward structure of the task was run as a within-participant factor.

-----Figure 4-----

As stated earlier, when the payoff matrix is asymmetric the reward and accuracy maximizing decision criteria are different, and in fact, a participant maximizing reward must sacrifice some measure of accuracy. Across a number of studies reviewed in Maddox (2002), we have found that participants have a bias toward accuracy maximization and only after extensive practice do they learn to shift away from this strategy toward a reward maximizing strategy. We interpret this “shift” away from accuracy toward reward as a form of cognitive flexibility. We predict that a regulatory fit between the situational focus and the reward structure of the task will lead to greater cognitive flexibility and thus to more nearly optimal decision criterion learning. Specifically, participants given a situational promotion focus under a gains reward structure and participants given a situational prevention focus under a losses reward structure should show better learning of the reward-maximizing decision criterion.

The location of the best fitting decision criterion relative to the accuracy and reward maximizing decision criterion is displayed in Figure 4b for each condition. Notice that the predicted interaction between situational focus and the reward structure of the task on decision criterion placement is supported by the data. Specifically, for the gain matrix, the best fitting decision criterion is closer to the reward maximizing criterion than to the accuracy maximizing criterion for the situational promotion focus participants (a regulatory match) than for the situational prevention focus participants (a regulatory mismatch). Similarly, for the loss matrix, the best fitting decision criterion is closer to the reward maximizing criterion than to the accuracy maximizing criterion for the situational prevention focus participants (a regulatory match) than for the situational promotion focus participants (a regulatory mismatch).

Although only a single study, these data suggest that the notion that regulatory fit leads to greater cognitive flexibility is fairly general and applies across traditional perceptual classification learning tasks (as outlined in detail in previous sections) and related tasks such as decision criterion learning. These data also suggest that the notion of cognitive flexibility can be instantiated in different ways depending upon the nature of the task. Regardless of the task, though, cognitive flexibility seems to open the participant up to examining alternative, and often less salient, strategies such as applying a complex conjunctive rule when simple uni-dimensional rules yield good (albeit sub-optimal) performance (as in Maddox et al, in press) or abandoning a bias toward accuracy maximization in favor of reward maximization (as in Markman et al, in press).

### **VIII. Summary and Future Directions**

This chapter offers a framework for examining the motivation-classification learning interface. We take as our initial model of classification learning, Ashby et al’s (1998) COVIS model that postulates two category learning systems: an explicit, hypothesis-testing system and an implicit, procedural-based learning system. COVIS assumes that rule-based category learning is dominated by the explicit hypothesis-testing system that uses working memory and executive attention and is mediated by a circuit that includes the anterior cingulate, the prefrontal cortex, and the head of the caudate nucleus, and that information-integration category learning is dominated by the implicit procedural-based learning system that is mediated largely within the tail of the caudate nucleus.

We take as our initial model of motivation, regulatory focus theory that postulates two forms of regulatory focus: a promotion focus that activates an approach mode of processing, and a prevention focus that activates an avoidance mode of processing. Following Higgins and colleagues (Crowe & Higgins, 1997; Higgins, Roney, Crowe, & Hymes, 1994; Shah, et al, 1998), we assume that a regulatory fit between two aspects of regulatory focus -- situational focus and the reward structure of the task -- is predictive of classification learning performance. Situational focus has to do with the global aspects of the person's classification learning environment and whether they are focused on performing well in the task in order to gain some reward (situational promotion focus), or in order to avoid losing some reward (situational prevention focus) upon task completion. The reward structure of the task has to do with the local aspects of the person's trial-by-trial classification learning environment and whether they are focused on maximizing the number of points gained on each trial (gains reward structure) or are focused on minimizing the number of points lost on each trial (losses reward structure) in order to achieve the global task goal.

We extend the notion of regulatory fit to classification learning by hypothesizing that a regulatory fit between situational focus and the reward structure of the task increases cognitive flexibility. The hypothesis leads to two strong predictions. First, regulatory fit should lead to better rule-based classification learning when cognitive flexibility is advantageous for solving the task, but should lead to worse rule-based classification learning when cognitive flexibility is not advantageous. Second, regulatory fit manipulations should affect the hypothesis-testing classification system, but not the procedural-based learning classification system. By extension, regulatory fit manipulations should affect rule-based classification learning more than information-integration category learning.

Two studies outlined in Maddox et al (in press) and one pilot study summarized in this chapter provides initial support for the first prediction. When the reward structure involved gains, Maddox et al (in press) found better rule-based classification learning for situational promotion participants than situational prevention participants when cognitive flexibility was advantageous, but found the opposite pattern when cognitive flexibility was disadvantageous. In a pilot study reviewed above where the reward structure involved losses and cognitive flexibility was advantageous, we found better category learning for the situational prevention participants (i.e., those with a regulatory fit) than for the situational promotion participants. The analogous study in which cognitive flexibility is disadvantageous is currently being investigated.

A pilot study provides initial support for the second prediction. In an information integration task where the reward structure involved gains, situational promotion participants showed greater cognitive flexibility than did situational prevention participants. Cognitive flexibility in this case led the regulatory fit participants to abandon hypothesis-testing strategies later in the session than participants with a regulatory mismatch. Future work needs to address the situation in which there is a regulatory fit between situational focus and a losses reward structure.

We also applied our regulatory fit hypothesis to a decision criterion learning task in which the reward structure involved gains or losses, but also included a bias toward one category over the other (Markman et al, in press). Under these conditions, the participant whose goal is to maximize gains or minimize losses must sacrifice some measure of overall accuracy (Maddox, 2002). In this case, cognitive flexibility would be associated with a greater willingness to sacrifice accuracy, which appears to be an almost universal bias in these cases, in the interest of gain maximization or loss minimization. As predicted, participants in a regulatory fit condition -- situational promotion focus with gains or situational prevention focus with losses -- learned to apply a decision criterion that was closer to the optimal criterion and farther from the accuracy maximizing decision criterion than participants with a regulatory mismatch.

#### **A. Regulatory Fit, Cognitive Flexibility and the Anterior Cingulate**

In section III.B we suggested that the anterior cingulate, a frontal brain structure utilized by the hypothesis-testing system, is critically involved in the selection of alternatives. To be specific, our

hypothesis is that regulatory fit leads to greater cognitive flexibility through increased anterior cingulate involvement. In this section we provide evidence in support of this claim.

Several lines of research support this claim. First, Ashby, Isen and Turken (1999; see also Isen, 1993, 1999) proposed a neuropsychological theory of positive affect that assumes that positive affect increases dopamine release from the ventral tegmental area (VTA) into frontal brain areas, in particular the anterior cingulate. As one test of this hypothesis they cite work showing that a mild positive affect manipulation leads participants to generate more “associates” in the Remote Associates Task (RAT; M.T. Mednick, Mednick & Mednick, 1964). Although regulatory fit and positive affect are not equivalent, many manipulations of positive affect involve a gain for subjects (such as an unexpected gift), and so they often involve a promotion focus. Second, in a recent pilot study, we (Baldwin, Markman, & Maddox, unpublished data) showed that a specific type of regulatory fit (i.e., a situational promotion focus versus a situational prevention focus along with instructions to maximize the number of associate generated) led the participant to generate more correct associates in the RAT, especially for the most difficult items. This result mirrors that for positive affect. Third, using ERP Amodio, Shah, Sigelman, Brazy and Harmon-Jones (2003) showed a relationship between chronic regulatory focus and activation in frontal brain areas.

We acknowledge that the proposed link between regulatory fit, cognitive flexibility, and frontal brain areas (in particular the anterior cingulate) is loose and speculative at this point. Even so, it provides a nice framework within which to examine the motivation-classification learning relation. Perhaps more importantly, it suggests a number of possible directions for future research and a number of potential connections with other cognitive functions, as well as emotional, motivational and personality traits. We briefly examine some of these issues next.

## **B. Future Directions**

### **1. VTA Neurobiological Connectivity**

What follows if regulatory fit increases dopamine release from the VTA? As outlined above, the VTA projects directly into the anterior cingulate which is a fronto-cortical brain structure strongly implicated in flexible cognitive processing. The VTA projects directly to a number of other important brain structures as well. Most relevant to cognition, the VTA projects directly to the prefrontal cortex, which is known to be involved in working memory (for a review see Goldman-Rakic, 1987, 1995), and to the hippocampus (mostly CA1; Gloor, 1997), which is thought to be necessary for episodic memory consolidation (e.g., Gluck & Myers, 1997; McClelland, McNaughton, & O’Reilly, 1995). The VTA also projects to brain regions that have been implicated in emotions and personality. For example, the VTA projects directly to the amygdala. The amygdala is reciprocally connected to the hippocampus and to the orbitofrontal cortex (Gloor, 1997). The amygdala is thought to play a key role in the memory system for emotional events and stimuli (Cahill & McGaugh, 1998). As a final, related, note, it is worth mentioning also that the amount of dopamine available in the brain declines with normal aging (Gabrieli, 1995). This might partially explain the common finding that elderly people tend to be less cognitively flexible. An exciting avenue for future research would be to apply the notion of regulatory fit in normal aging with the ultimate goal of increasing (at least phasically) dopamine release to increase cognitive flexibility.

This brief review is not meant to be complete, nor is it meant to motivate a set of specific predictions. Rather, we include it to emphasize the value of even a crude theory of the neurobiological underpinnings of the motivation-cognitive interface. If a regulatory fit leads to increased cognitive flexibility by increasing dopamine release from the VTA then this has implications not only for the processes associated with the anterior cingulate, but also for processes associated with the prefrontal cortex, the hippocampus, the amygdala, and likely the many other brain regions indirectly connected to the VTA (e.g., orbitofrontal cortex, the head of the caudate nucleus, etc). It is clear from this brief review that these brain regions include those involved directly in cognition but also those involved in emotion, motivation and personality.

### **2. Applications to Related Cognitive Tasks**

The notion that regulatory fit leads to increased cognitive flexibility should be examined in other cognitive tasks for which cognitive flexibility is advantageous or disadvantageous. Applications to tasks such as solving anagrams and finding remote word associates have already been conducted, but a number of more sophisticated tasks are available in the literature. For example, many studies examine tasks that involve repeated task switches (e.g., Mayr, Diedrichsen, Ivry, & Keele, in press). In tasks of this sort demands for flexible cognitive processing are high, because of the need for shifts in attentional focus. In addition, the prefrontal cortex has been implicated in many of these tasks and based on the VTA-prefrontal cortex projection described above should be affected by regulatory fit manipulations. We are beginning to explore this domain.

A second task worth exploring is the so-called Bechara (or Iowa) gambling task (Bechara, Damasio, Damasio, & Anderson, 1994). On each trial in this task, the participant must select a card from one of four decks. The decks differ in the magnitude of gains and losses and in their long run expected reward. Like task switching, the Bechara task has been studied extensively in brain-damaged individuals including those with prefrontal cortex, amygdala and orbitofrontal damage. Because the neural circuits involved in this task are being elucidated, this task may prove useful in extending our knowledge about the neurobiology of regulatory focus theory, and ultimately lead to a deeper understanding of the motivation-learning interface.

### **3. Relation to Reinforcement Sensitivity Theory**

Regulatory focus theory and the notion of regulatory fit have proved quite useful in our quest to examine the motivation-learning relation. Other “motivation-learning” theories have been developed. One that stands out is Reinforcement Sensitivity Theory (RST; Gray, 1982, 1987; Pickering & Gray, 2001). The details of the theory are beyond the scope of this chapter but, briefly, RST assumes that there are a small number of large-scale neural systems that control responding to motivationally significant reinforcers. RST proposes two systems: a behavioral approach/activation system (BAS) and a behavioral inhibition system (BIS). The BAS is supposed to mediate both approach and avoidance behaviors, and is most relevant to regulatory focus theory. The BAS is activated by rewarding stimuli and the output of the system increases the probability of approach toward the desired goal. One novel aspect of the theory is that it makes direct links to personality research. Specifically, the theory proposes that the biological basis of fundamental personality traits is a function of individual differences in the sensitivity of the BAS system. In other words, people with high levels of BAS-related personality traits have a more responsive BAS than people low in BAS-related traits, and thus will experience stronger motivational and reinforcing effects. Although there is some controversy over which personality traits are BAS-related, impulsivity, sensation-seeking, and extraversion have all been suggested (see Pickering and Gray, 2001 for a review).

Neurobiologically, it has been suggested that the BAS is located within brain regions innervated by dopamine producing cells (Gray, 1987; Pickering & Gray, 1999). This latter connection makes RST especially relevant to our current focus as we also place a high premium on dopamine mediated processes. To date, no attempt has been made to directly link regulatory focus theory and RST, and this chapter is not an appropriate avenue for such an attempt. Even so, there is clearly significant overlap between the two approaches and future work should attempt a more direct comparison.

### **4. Chronic Focus and Other Personality Characteristics**

The studies reviewed in this chapter experimentally manipulated situational focus and the reward structure of the task. Chronic focus was not examined and cannot be experimentally manipulated. Rather chronic focus is a personality factor that the person brings with them into their environment. As suggested by the work reviewed in Section II, chronic focus is known to interact with situational focus and the reward structure of the task under some conditions. A complete understanding of the motivation-classification learning interface requires that personality factors such as chronic focus be included. It is very likely that the regulatory fit effects that we observed between situational focus and the reward structure of the task will be enhanced or diminished by a match or

mismatch, respectively, with chronic focus. Future research should include measures of chronic focus and should expand the definition of regulatory fit proposed in this chapter (for relevant work, see Higgins, Shah & Friedman, 1997; Idson, Liberman, & Higgins, 1999).

Extensions to other personality measures such as depression, anxiety, etc should also be undertaken. Again the fact that the VTA projects directly or indirectly to so many brain regions that have been implicated in emotion and personality suggests that a more complete understanding of the motivation-learning interface will be obtained if this work is extended. Expanding the scope of this work will increase our understanding of the interdependence of personality, motivation and cognitive factors in predicting behavior (e.g., Idson, Liberman, & Higgins, 1999).

### **5. Behavioral, Patient and Brain Mapping Approaches to Studying the Motivation-Learning Interface**

The motivation-learning framework developed in this chapter could have been described with little (if any) reference to the brain. From a social and/or cognitive psychological perspective this is adequate. In fact, because our data are collected from normally functioning individuals and are purely behavioral some might argue that we should not make reference to the brain. We disagree. In our view, behavioral research of the sort presented in this chapter is informative to the cognitive neuroscience community, and more importantly can help bridge the artificial gaps between the study of interdependent processes (e.g., motivation and cognition) that preclude a full understanding of human behavior. Our approach is to extract from the vast neuroscience literature a set of conditions and constraints. We then outline an admittedly crude set of neurobiological underpinnings, but these lead to a surprisingly rich and testable set of neurobiologically inspired predictions. Without reference to the underlying neurobiology we would not be left with all the potential future directions outlined above.

Some might argue that one cannot make significant progress toward understanding the motivation-learning interface and the neurobiological underpinnings without examining patient with brain lesions or asking people to participate in an fMRI study. Again, we disagree. Significant scientific contributions can be made to cognitive neuroscience research using behavioral techniques like those presented in this chapter, as well as by using patient with brain damage as participants or by using fMRI. Each has something unique to offer and the goal should be to identify points of convergence across approaches.

Indeed, there are a number of problems with the research program of localizing cognitive processes in the brain. As Uttal (2001) points out, there is a tendency to start the process of identifying brain regions by associating them with cognitive tasks that stand in for fundamental cognitive processes. However, the brain itself contains richly interconnected regions that are unlikely to respect the task divisions imposed by psychologists. Thus, developing integrative theories of the relationship between motivation and cognition based on behavioral evidence is a crucial step in the cognitive neuroscience program, even when none of the main dependent measures involve imaging or the use of data from brain-damaged patients.

### **IX. Closing Remarks**

Our goal in writing this chapter was two-fold. Our first goal was to offer a viable approach to studying the interface between research on motivation and classification learning. The hypothesis that a regulatory fit between situational focus and the reward structure of the task leads to greater cognitive flexibility provides a first step toward achieving this goal. Our second goal was broader in scope. We hope that the framework and empirical tests outlined in this chapter will lead to a renewed interest in bridging the artificial gap that has formed between research focused on motivation and research focused on learning. In the 1950's and 1960's learning and motivation research was intimately related and much progress was made (Miller, 1957, 1959; Young, 1959). Since that time, work on motivation and learning has diverged. Most research on motivation in humans has been done in social and educational psychology. In contrast, research on learning was generally pursued by cognitive and animal psychology. This separation is artificial and (in our view) detrimental to the advancement of a

complete understanding of behavior. After all, the title of this book series is “The Psychology of Learning AND Motivation (emphasis added)”. The work outlined in this chapter focuses on learning and motivation. We hope that other researchers will follow suit and more openly recognize in their work the intimate relationship between these two psychological factors.

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Table 1. Regulatory Fit-Classification Learning Predictions

	Reward	Promotion	Prevention
Task Type	Structure	Focus	Focus
Rule-based: Flexibility	Gains	Better	Worse
Rule-based: Flexibility	Losses	Worse	Better
Rule-based: No flexibility	Gains	Worse	Better
Rule-based: No flexibility	Losses	Better	Worse
Information Integration	Gains	Worse?	Better?
Information Integration	Losses	Better?	Worse?

Note: The “?” denote a more speculative prediction.

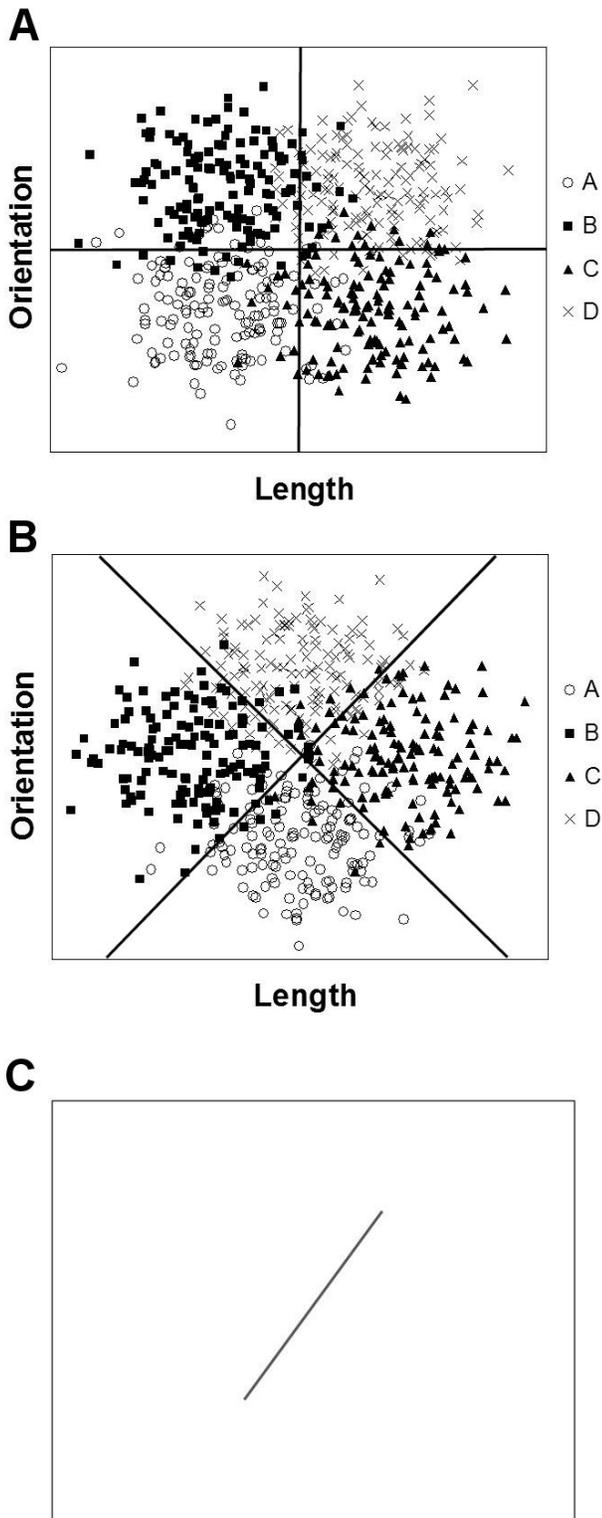


Figure 1. (a) A four-category rule-based category structure with two dimensions: line length (in pixels) and orientation (in degrees). (b) A four-category information-integration category structure, created by rotating the rule-based structure 45 degrees counter-clockwise. (c) a representative stimulus.

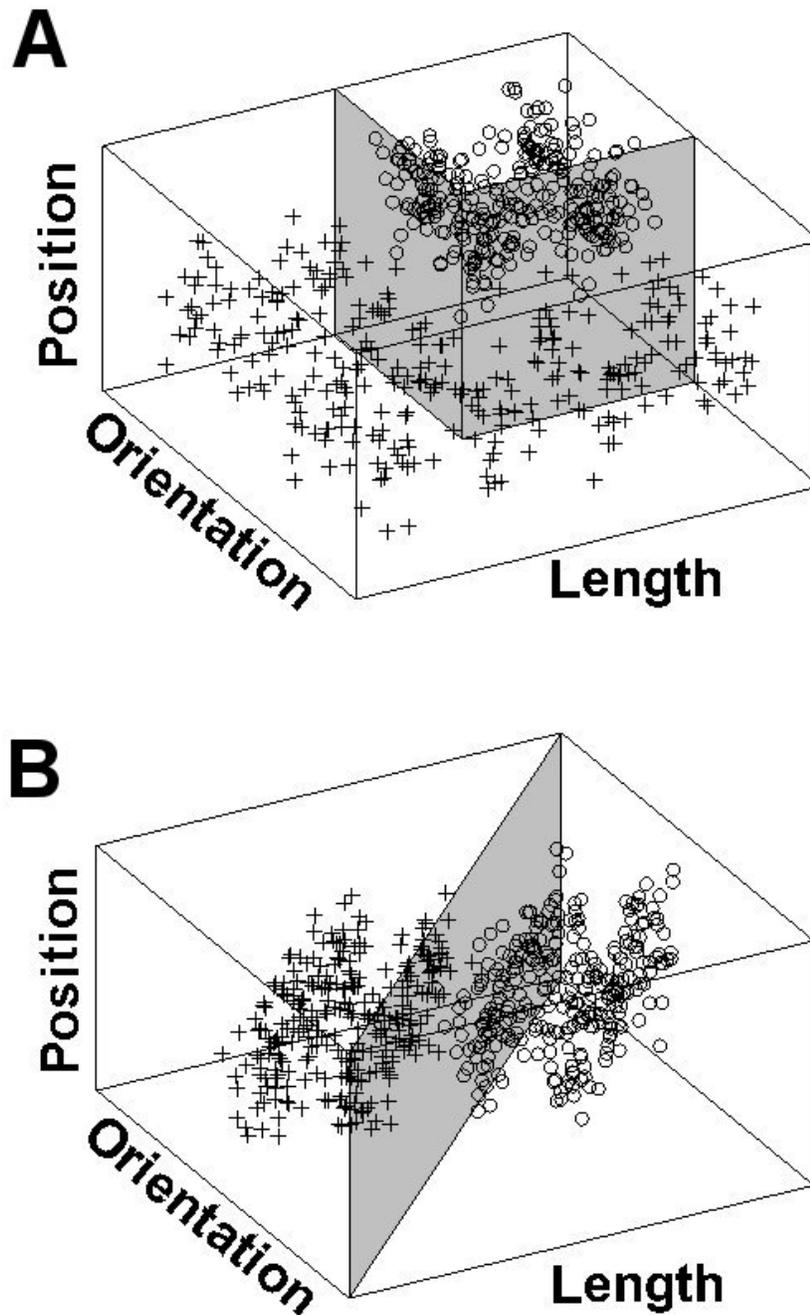


Figure 2. (a) The two-category conjunctive rule-based category structure used in Maddox et al (in press), Experiment 1. (b) A two-category information-integration category structure. In both panels, plus signs (+) denote category A, open circles (O) denote category B, and the grey planes represent the optimal decision bound. Copyright Psychonomic Society, Inc., 2006. Adapted with permission.

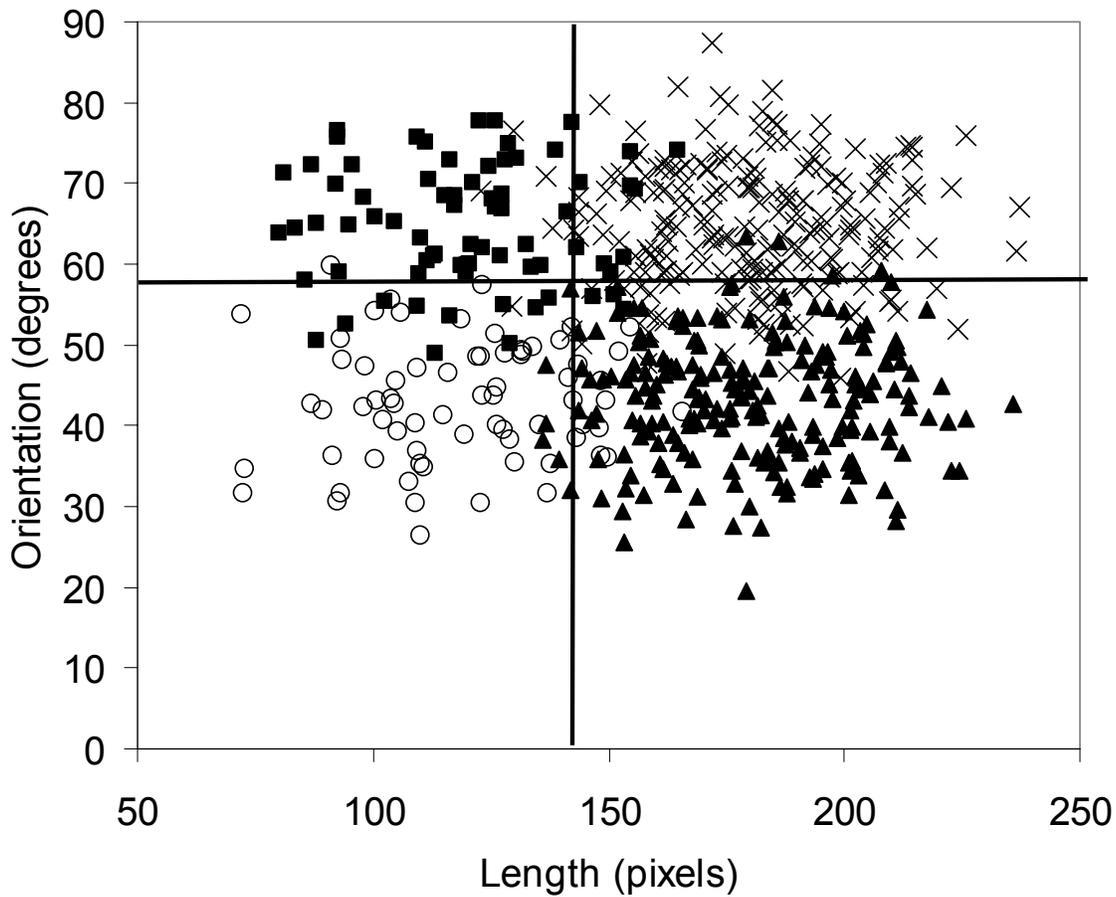


Figure 3. Scatter-plots of the stimuli along with the optimal decision bounds from the four-category conjunctive, rule-based category structure from Maddox et al (in press), Experiment 2. Open circles denote stimuli from category A. Filled squares denote stimuli from category B. Filled triangles denote stimuli from category C. X's denote stimuli from category D. Copyright Psychonomic Society, Inc., 2006. Adapted with permission.

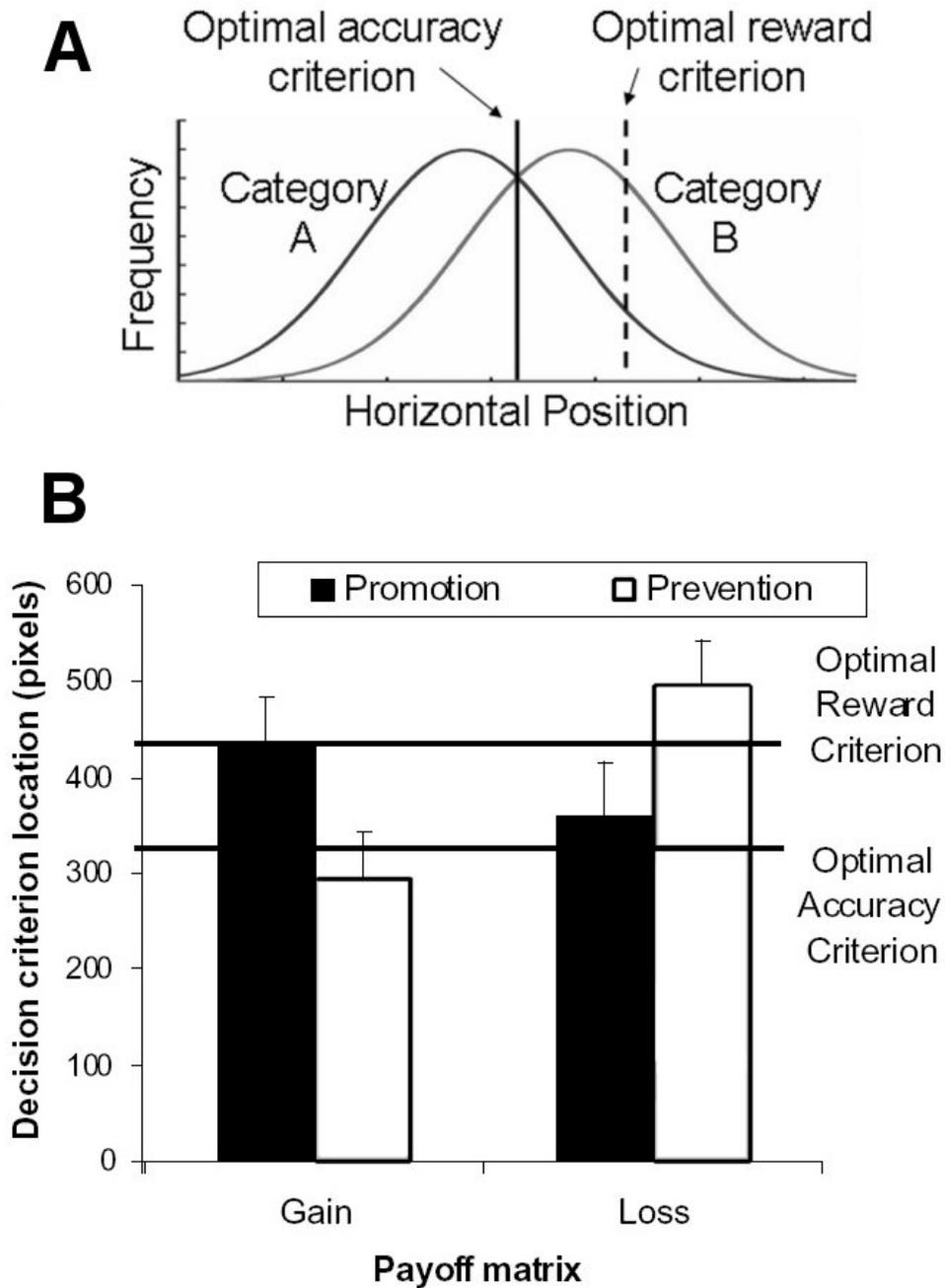


Figure 4. (a) Category distributions and optimal reward and accuracy decision criteria from Markman et al (in press). (b) Decision criterion estimates (averaged across participants). Copyright Blackwell Publishing, Inc., 2005. Adapted with permission.