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Using Regulatory Focus to Explore Implicit and Explicit Processing in Concept Learning

Abstract: *Complex cognitive processes like concept learning involve a mixture of redundant explicit and implicit processes that are active simultaneously. This aspect of cognitive architecture creates difficulties in determining the influence of consciousness on processing. We propose that the interaction between an individual's regulatory focus and the reward structure of the current task influences the degree to which explicit processing is active. Thus, by manipulating people's motivational state and the nature of the task they perform, we can vary the influence of conscious processing in cognitive performance. We demonstrate the utility of this view by focusing on studies in which people acquire new perceptual concepts by learning to classify them. This technique will allow us to better tease apart the roles of explicit and implicit processing in a variety of cognitive tasks.*

As Cognitive Psychologists, we are often led astray by the labels we place on our phenomena. We study processes like attention, concept formation and memory. By giving each of these processes a label, we reify it and thereby give it more unity than it may deserve. What research is beginning to make plain, however, is that the traditional labels used by cognitive psychologists refer to input-output relationships

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that may be served by many underlying cognitive and motivational processes (Uttal, 2001). For example, memory involves encoding information about some experience in a manner that permits it to influence later processing. The general consensus within the memory literature is that this ability is served by multiple memory systems (Ashby & Waldron, 1999; Packard & Cahill, 2001; Roediger, 2003).

Two aspects of this situation complicate the study of cognitive processing. First, the suite of mental systems that serve different functions all operate simultaneously. Thus people's performance in a task is a reflection of multiple systems operating together. At times these systems may lead to the same response, and at times they may suggest different responses (Sloman, 1996). Teasing apart the contribution of these systems is a difficult process. Second, these systems differ in their conscious accessibility. Some systems are explicitly mediated, while others operate only implicitly.

So, a complete model of a task requires understanding the component cognitive processes, their relationship to conscious processing and the factors that engage these processes. In this article we describe a research programme designed to address this question by focusing on the interaction of motivation and cognition in perceptual classification learning. This domain is particularly apt because we understand a lot about the component processes involved in classification learning. In addition, our research on motivation suggests that different motivational conditions can affect the relative use of implicit and explicit processes in learning.

In the next section we discuss our framework for perceptual category learning. Then we present a motivational framework that addresses the role of implicit and explicit systems in learning. Next we illustrate the utility of this framework with studies in which people acquire new perceptual concepts by learning to classify them. Finally we demonstrate how this framework can be extended to other cognitive processes.

Perceptual Classification

We are interested in classification learning because it is known to involve a mix of conscious and unconscious processes. Classification is the ability to take a set of items and to determine the category to which they belong. Thus, classification learning requires learning an underlying representation (or concept) that binds together members of the same category. There is a long history of using people's ability to learn to classify new items as the empirical basis for models of categorization

(Medin & Schaffer, 1978; Nosofsky, 1986; Posner & Keele, 1970). Although there are many tasks one might use to study category representations (see e.g. Markman & Ross, 2003), classification learning has the advantage that the processes involved in acquiring new perceptual categories are reasonably well understood (Ashby & Maddox, 2005). Furthermore, there are good mathematical modelling tools that can be used to characterize the performance of individual subjects and how that performance changes over the course of a study (Maddox & Ashby, 2004).

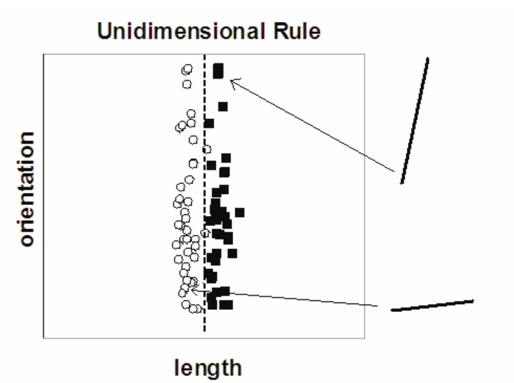
In a typical perceptual classification task, two classes (or groups) of simple perceptual stimuli are constructed by the experimenter with one class of items being associated with category A and the second with category B. On each trial of a typical task, one stimulus is sampled randomly from the set of all stimuli and is presented to the subject. The subject studies the item and assigns it to one of the two categories by pressing either the key associated with category A or the key associated with category B. Following the response the subject receives feedback regarding the correctness of their response.

Over the past several years, there has been much research supporting the notion that different category structures are learned by different systems, each of which has a unique neurobiological underpinning. Empirical support comes from a wide range of research areas including animal learning, neuropsychology, functional neuroimaging and cognitive psychology (see Ashby & Maddox, 2005; Keri, 2003, for a review).

One multiple-systems model that has stimulated much research is the COmpetition between Verbal and Implicit Systems (COVIS) model of perceptual classification learning (Ashby, *et al.*, 1998; Ashby, Isen & Turken, 1999). This model postulates two systems that compete throughout learning. One system is an explicit, hypothesis-testing system that uses working memory and executive attention to select and test specific hypotheses. This system is mediated predominantly by frontal brain regions. The second system is an implicit, procedural-based learning system that learns to associate a category response with a region of perceptual space. A critical brain structure in this system is the striatum (a subcortical structure) that is assumed to provide a low-resolution map of the perceptual stimulus space. This system learns to associate sub-regions of perceptual space with category assignments through a gradual and incremental learning process. Of particular interest to the current discussion is the fact that processing in the explicit hypothesis-testing system is available to conscious awareness, whereas processing in the implicit, procedural-based learning system is not.

The hypothesis-testing system is assumed to mediate the learning of rule-based categories. *Rule-based* classification learning tasks are those in which the category structures can be learned via some explicit reasoning process. Frequently, the rule that maximizes accuracy (i.e. the optimal rule) is easy to describe verbally. For example, Figure 1a presents a scatter-plot of stimuli from a rule-based condition with two categories. Each point in the plot denotes the length and orientation of

(a)



(b)

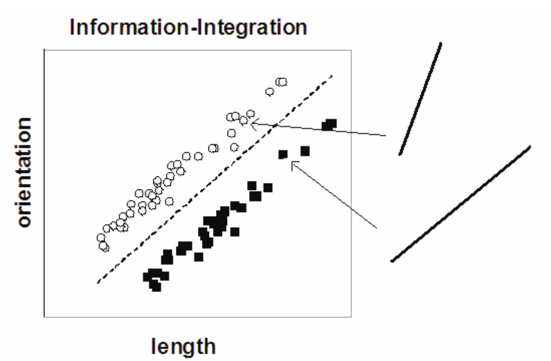


Figure 1. Simple (a) rule-based and (b) information integration category structures using two-dimensional stimuli. The dimensions are the length and orientation of a single line. The figure shows a sample of stimuli from two regions of space. The rule-based structure is unidimensional because only one of the two stimulus dimensions is relevant. Open circles denote stimuli from category A and filled squares denote stimuli from category B.

a single line stimulus, with different symbols denoting different categories. A sample stimulus from each category, along with its associated point representation in the scatterplot, is also displayed. The broken line denotes the optimal decision bound. In this example, the rule is to give one response to ‘short’ lines and a second to ‘long’ lines.

The procedural-based learning system is assumed to mediate the learning of information-integration categories. *Information-integration* category learning tasks are those in which accuracy is maximized only if information from two or more stimulus components (or dimensions) is integrated at some pre-decisional stage (Ashby & Gott, 1988). For example, Figure 1b presents a scatter-plot of stimuli from an information-integration condition with two categories. The broken line denotes the optimal decision bound. It has no verbal or rule-based analogue because length and orientation are measured in different units. Although one can certainly state the rule as, ‘respond A if the orientation is greater than the length; otherwise respond B’, it is unclear how to interpret the term ‘greater than’ because the dimensional values are measured in different units, so this type of decision rule makes no sense to naïve participants.

An advantage of the perceptual classification learning task is that a large amount of data is collected from each subject, and thus all analyses can be performed at the individual-subject level. Two levels of analyses are always conducted. First, accuracy-based analyses that include estimating learning curves and performing ANOVA are conducted. Second, a series of quantitative models are applied that provide useful insights into the types of decision strategies that subjects are using. The model-based analyses are important because qualitative differences in strategy are not always identifiable at the level of accuracy. This follows because it is often the case that two qualitatively different models can yield identical accuracy rates (see e.g. Maddox, Markman & Baldwin, 2006). In our modelling approach we fit a number of different decision bound models to each subject’s responses on a block by block basis. Decision bound models are a standard and very useful tool in classification research (e.g. Ashby, 1992; Ashby & Gott, 1988; Maddox & Ashby, 1993). Decision bound models assume that the subject partitions the perceptual space into response regions. On each trial, the subject determines which region the percept is in, and then emits the associated response.

Two classes of decision bound models are generally applied. One class of models assumes that the subject uses an explicit hypothesis-testing strategy. Using the Figure 1a condition as an example, these include a model that assumes that the subject uses the optimal decision criterion along the length dimension, a model that assumes that the subject uses a sub-optimal decision criterion (where the decision criterion is freely estimated from the data) along the length dimension, and a model that assumes that the subject uses a sub-optimal decision criterion along the orientation dimension. The same models might be applied to the Figure 1b conditions, but in addition models that instantiate conjunctive rules might also be applied. For example, the subject might set a criterion along the length dimension (whose value is estimated from the data) and a criterion along the orientation dimension (whose value is estimated from the data) and might respond 'A' to short, steep lines and respond 'B' to all other lines. The second class of models assumes that the participant uses an implicit procedural-based learning strategy (see Maddox & Ashby, 1993 for details).

Although a number of these strategies are possible, we focus on models that assume a linear decision bound of arbitrary slope and intercept (freely estimated from the data). Each model also has one 'noise' parameter that captures the variability in the memory for, or application of, each rule. Well-understood statistical procedures exist for determining how to select the best-fitting model from among a set of competitors (Ashby, 1992; Wickens, 1982).

Regulatory Focus and Cognitive Processing

Research on cognition has typically focused on information processing in a variety of tasks. Motivational factors — those that drive individuals to action — are not typically explored. It is becoming clear in a variety of domains, however, that motivational processes are crucial for understanding cognitive processes. Without motivation, people will not act at all (Carver & Scheier, 1998). Furthermore, behaviour changes radically under different motivational circumstances. For example, many observed cultural differences in reasoning may be attributed to motivational factors that differ across cultures (Briley & Wyer, 2002; Hong & Chiu, 2001; Kim & Markman, 2006). Furthermore, changes in motivational states can alter the choices people make and the processes they use to reach decisions (Higgins *et al.*, 2003; Loewenstein, 1996).

We are particularly interested in regulatory focus theory as a motivational framework (Higgins, 1997; 2000). This view builds from the observation that organisms have two psychologically distinct kinds of goals: *approach* goals and *avoidance* goals. Approach goals are desirable states of the world that the individual desires to achieve. Avoidance goals are undesirable states of the world that the individual desires to avoid. In addition to the pursuit of specific approach and avoidance goals, Higgins (1997) suggests that the motivational system may be tuned to a state of readiness for potential gains or losses in the environment. In particular, an individual may have a *promotion focus*, which involves sensitivity to potential gains and nongains in the environment, or an individual may have a *prevention focus*, which involves sensitivity to potential losses and nonlosses in the environment.

There are two ways that these regulatory foci can be engaged. First, individuals have a chronically accessible regulatory focus. That is, they have a predisposition to be in either a promotion of a prevention focus (Higgins, 1987). In addition, situations may induce a regulatory focus. In particular, when people are pursuing a particular approach goal, they often have an active promotion focus. Similarly, when people are pursuing an avoidance goal, they often have an active prevention focus. The goals that lead to active regulatory foci can be pursuits of external rewards and punishments, social rewards and punishments, or the desire to achieve particular internal states (e.g. to reduce anxiety).

Of particular interest is that regulatory focus interacts in an interesting way with the feedback people receive while performing a task. The tasks that we give people in the laboratory have a reward structure. For example, in many psychology experiments people are given points or have points taken away from a score over the course of the task. The total score someone achieves is frequently related to performance bonuses. At a minimum, participants are told to do their best, and so there is a social contract between the participant and the experimenter. Thus, gains of points are a mild reward and losses of points are a mild punishment on each trial of the study.

Just from this analysis, we can see that the overall regulatory focus of a participant may fit or mismatch with the reward structure of the task. Specifically, if someone has a promotion focus, then there is a regulatory fit if they receive points (or are rewarded) while performing the task, but a regulatory mismatch when they lose points (or are punished) while performing the task. Conversely, if someone has a prevention focus, then there is a regulatory fit if they lose points (or are punished) while performing the task, but a regulatory mismatch if they gain points (or are rewarded).

What are the consequences of a regulatory fit? Higgins and colleagues (Higgins, 2000, 2005; Higgins *et al.*, 2003) suggest that regulatory fit induces a feeling of fluency that enhances people's preferences. In our research, we have expanded this proposal (Maddox, Markman &

Baldwin, 2006; Markman *et al.*, 2005). We draw a parallel between the circumstances of regulatory fit and those that induce positive affect (Ashby, Isen & Turken, 1999; Isen, 2001; Isen & Labroo, 2003). Often, in studies of positive affect, participants get an unexpected reward that matches their promotion focus. Neuropsychological theories of positive affect suggest that positive affect increases dopamine release from the ventral tegmental area (VTA) into frontal brain areas, in particular the anterior cingulate (Ashby, Isen & Turken, 1999).

Dopamine release in these frontal areas is thought to promote more flexible cognitive processing. One finding consistent with this view comes from work using the Remote Associates Task (RAT) (Mednick & Mednick, 1967), a test in which people are given three words that are all related to a fourth word, typically in a distant way. Subjects must find the related word. For example, the words ENVY, GOLF and BEANS are all related to the word GREEN. Ashby, Isen & Turken (1999) report data in which people given a manipulation of positive affect solved more of these problems than did those who did not receive this manipulation. We obtained a parallel result using a manipulation of regulatory fit. We drew our items from three previous studies and we selected seven items designed to be easy, seven designed to be of moderate difficulty, and seven designed to be hard (Bowers *et al.*, 1990; Dorfman *et al.*, 1996; Mednick & Mednick, 1967).

For the purposes of this task, we assume that finding a remote associate is intrinsically rewarding, and so the task itself gives positive feedback for correct responses. Thus, the RAT should lead to a regulatory fit for subjects with a promotion focus and a regulatory mismatch for subjects with a prevention focus. We added the RAT to an unrelated study that manipulated regulatory focus by having subjects perform a task with the prospect of obtaining an entry into a draw to win $50. In our study, seventeen subjects were given a promotion focus. They were told that if they performed well on the unrelated task, they would get an entry. In addition, nineteen subjects were given a prevention focus. They were given an entry ticket when they arrived at the lab and were told that they could keep the ticket if they performed well on the unrelated task. This manipulation has been used successfully in previous studies of regulatory focus (Shah & Higgins, 1997).

The mean proportion of items correctly solved by subjects with a promotion and prevention focus is shown in Table 1. Of interest, participants solve about the same proportion of the items overall in the promotion ($M = 0.20$) and prevention ($M = 0.19$) focus conditions. Where these groups differ is in the difficulty of the items they solve.

We contrasted the proportion of items solved within each type using t-tests. The only reliable difference is that promotion subjects solved a significantly higher proportion of the hard items ($M = 0.10$) than did the prevention subjects ($M = 0.02$), $t(34) = 2.27$, $p < 0.05$. There was, however, a tendency for subjects with a prevention focus to solve more of the easy items ($M = 0.50$) than did subjects with a promotion focus ($M = 0.40$). These data are consistent with the suggestion that people are more strategic and flexible in their processing when they have a regulatory fit than when they have a regulatory mismatch, although obviously this task shows only the regulatory fit between promotion focus and tasks with positive rewards.

Table 1. Proportion of items solved in the Remote Associates Task as a function of Regulatory Focus

Regulatory Focus	Easy Items	Medium Items	Hard Items
Promotion Focus	0.40	0.21	0.10
Prevention Focus	0.50	0.20	0.02

To be clear, however, we are not arguing that regulatory fit induces positive affect, which in turn produces greater cognitive flexibility. Rather, we think that most prior studies of positive affect have induced a promotion focus that interacts with the reward structure of the task being performed. Often this task has a gains reward structure, so many studies of positive affect examine subjects in a state of regulatory fit. We do not think that subjects with a prevention focus in a task with losses will necessarily experience positive affect, but we do think they will show similar effects of regulatory fit to subjects with a promotion focus in a task with a gains reward structure.

The frontal systems implicated in these results are also associated with consciously accessible cognitive processes. Thus, an alternative way to look at these results is that conditions of regulatory fit lead to relatively greater involvement of explicit conscious processing than do conditions of regulatory mismatch. From our standpoint, then, this framework provides a method for changing the mix of explicit and implicit processes brought to bear on a task. In this way we can begin to tease apart the role of consciously accessible cognitive processes in normal thinking. In the next section, we review studies of perceptual classification that demonstrate the utility of this technique.

Studies of Regulatory Fit in Classification

Classification learning provides a good domain for testing the regulatory fit framework, because classification involves both explicit and implicit processes. As discussed above, the COVIS framework suggests that there are two distinct strategies that people use to learn new sets of categories. The hypothesis-testing system is clearly associated with consciously accessible processes. The system itself involves generating and testing explicit hypotheses, and subjects are able to report the rules they are using to classify with great accuracy. In contrast, the procedural-based learning system involves a more implicit similarity-based classification process. Learning is slow in this system. Furthermore, subjects cannot report the basis of their classification accurately. That is, while many subjects using a procedural-based learning strategy will state a rule that they are using to classify the items if asked, they are unable to do so accurately. This hypothesis seems broadly consistent with other neuropsychological approaches to consciousness (e.g. Crick & Koch, 1998).

We know from the research sketched above that normal individuals are able to use both of these strategies, and that both of them are typically brought to bear on a classification task. Indeed, information-integration tasks may be learned initially by the hypothesis-testing system and later performance may be supported by the procedural-based learning system.

If we are correct, and regulatory fit increases the involvement and effectiveness of hypothesis-testing processes in classification, then sets of categories that require learning complex explicit rules should be acquired more easily under conditions of regulatory fit than regulatory mismatch. Thus, if we examine people's responses in a complex rule-based learning task, they should be more accurate when there is a regulatory fit than when there is a regulatory mismatch. In addition, people should find the more complex rule that distinguishes among categories more quickly when there is a fit than when there is a mismatch.

Regulatory fit should not always lead to better performance, however. There are two conditions under which participants with a regulatory mismatch may outperform those with a regulatory fit. First, there are cases in which people are learning rule-based categories for which the task requires refining the application of the rule rather than a search for a complex rule. In this case, elaborate hypothesis testing will interfere with refining a simpler rule. Thus, when there is a regulatory fit, we should observe people trying a number of different rules, but when there is a mismatch, people should focus on a single strategy.

Second, when people are learning true information integration categories, then rules will not support accurate performance. In this case, people with a regulatory mismatch will learn faster and more accurately, because they will be less prone to try (sub-optimal) explicit rules, and will abandon the explicit hypothesis-testing system in favour of the procedural-based system earlier. Thus, when looking at the strategies that characterize people's performance, people with a regulatory mismatch should shift from the use of explicit rules (which will dominate early in processing) to the use of implicit procedural--based learning strategies. Because explicit processing is less prominent with a regulatory mismatch, this shift to procedural-based learning strategies should occur earlier in learning when there is a mismatch than when there is a match.

We have explored this set of predictions in a series of studies that provides basic support for the framework outlined here. First, we conducted studies with a complex rule-based task to test whether regulatory fit promotes explicit rule-based processing (Maddox, Baldwin & Markman, 2006). Stimuli for this study were lines varying in length, orientation and the horizontal position of the line on the screen. The items were divided into two categories (see Figure 3a). The items were set up so that good performance could be achieved by forming a rule along any one dimension. However, the learning criterion for this task was 90% accuracy. This level of accuracy could only be achieved by forming a conjunctive rule that combined the length and orientation dimensions. This pair of dimensions was chosen for the conjunctive rule, because pilot research with these items suggested that the position of the line on the screen was most salient. Thus, we expected that many subjects would begin by trying a simple rule based on the position of the line. In order to exceed the learning criterion, participants would eventually have to abandon this rule and form a different rule involving two other dimensions.

We manipulated regulatory focus in this task using an overall incentive for performance. Subjects given a promotion focus were brought to the lab and told that they would have a chance to win a ticket into a raffle for a one-in-ten chance to win $50. They were shown the raffle ticket they could win. They were told that they would be given this ticket if the number of points they had at the end of the last block of the learning task exceeded a criterion. This criterion was set to require 90% accuracy in responding across the last forty-eight trials of the experiment. Subjects given a prevention focus received similar instructions, except that they were given a raffle ticket for a draw to win $50 when they entered the lab and were told that they could keep the ticket provided their performance in the last block of trials exceeded the criterion.

Items were presented on a computer display as shown in Figure 2. The stimulus is presented in the window. Along the right side of the screen is a 'Point Meter' showing the subject the current number of points that they have obtained. This scale also shows the bonus criterion. The region above the criterion is labelled 'Yes' and the region below is labelled 'No' to make clear whether participants have exceeded the criterion. When participants make a correct response, the number of points given for a correct response is awarded and the sound of a cash register plays over the computer speakers. When the participants make an incorrect response, the number of points given for an incorrect response is awarded, and the sound of a buzzer plays. In addition, verbal feedback (the word 'Correct' or 'Incorrect') is shown at the bottom of the screen after each trial.

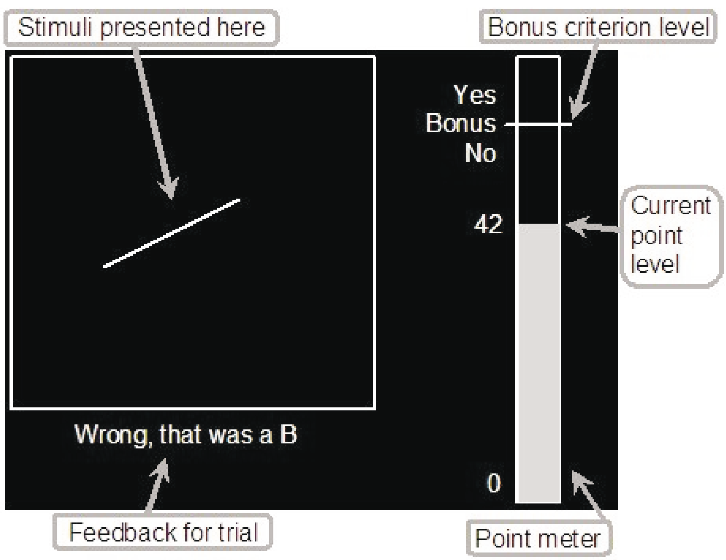
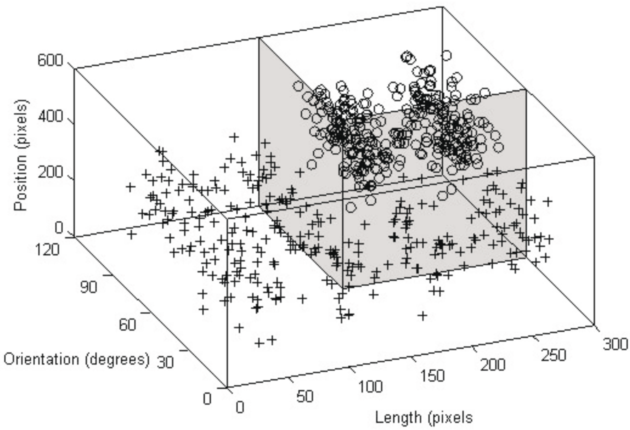


Figure 2. Annotated screen shot showing the computer interface used in the experiments.

(a)



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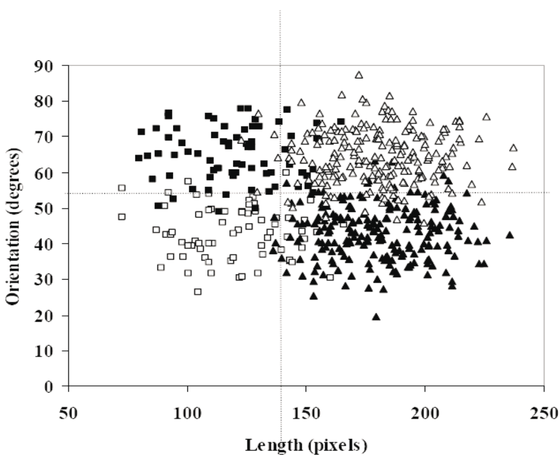

Figure 3. Category structures used in studies of regulatory fit. (a) A three-dimensional rule-based category structure with a low-salience conjunctive rule that requires flexibility to be learned. Open circles denote stimuli from category A and plus signs denote stimuli from category B. (b) A two-dimensional rule-based structure with categories that required less flexibility to learn. Open squares denote stimuli from category A, filled squares denote stimuli from category B, filled triangles denote stimuli from category C, open triangles denote stimuli from category D.

In the first version of the task that we ran, participants received points for correct responses. They were given two points for a correct response, and zero points for an incorrect response. They had to achieve a bonus criterion of eighty-six points in the last block in order to qualify for the raffle. Thus, for this version of the task, participants with a promotion focus had a regulatory fit and those with a prevention focus had a regulatory mismatch.

The data supported the prediction that regulatory fit promotes the use of explicit hypothesis-testing. Participants with a promotion focus were more accurate in their classification performance than were those with a prevention focus. This difference in accuracy was most prominent in the last few blocks of the study. Furthermore, a higher proportion of participants reached the learning criterion when they had a promotion focus than when they had a prevention focus. Finally, a variety of models were fitted to each subject's performance in each block. Typically, subjects' data were best fit by either unidimensional models or conjunctive models, indicating that everyone was using rules of some type. The difference is that subjects with a promotion focus began to use a conjunctive rule earlier in the study than did subjects with a prevention focus.

This pattern of data alone is ambiguous, because it could either reflect that promotion and prevention focus differ in their effects on cognitive processing, or it could reflect differences between regulatory fit and regulatory mismatch. To distinguish between these possibilities we ran a second study that was identical to the one just described, except that participants lost points on each trial (Maddox, Baldwin & Markman, 2006). Participants lost three points for an incorrect response but only one point for a correct response. In this case they started the study with zero points. The point meter moved downward as points were lost. The performance criterion in this case was –58 points. Thus, for this version of the study, subjects with a prevention focus have a regulatory fit and those with a promotion focus have a regulatory mismatch.

As predicted by regulatory fit, the results of this study are the mirror image of those just described. In this study, participants with a prevention focus were more accurate than were those with a promotion focus. Similarly, participants with a prevention focus were more likely to reach the learning criterion than were those with a promotion focus. Finally, participants with a prevention focus found a conjunctive rule faster than did those with a promotion focus. Thus, regulatory fit appears to engage explicit rule-based processing more strongly than does regulatory mismatch.

We have also identified situations in which a regulatory mismatch is advantageous for performance. In one study, we gave participants a task for which extensive hypothesis testing is disadvantageous. In this task, participants were asked to learn to distinguish between four categories. Once again, the stimuli were lines that differed in their length and orientation (all stimuli were presented centred on the screen and thus did not differ in position). As shown in Figure 3b, the categories were distinguished by values on a conjunction of length and orientation with each category occupying a different quadrant of stimulus space. These categories overlapped, so that optimal accuracy was only 77%. Thus, what made this task difficult was not finding a rule, but rather sticking with the set of rules long enough to establish good performance.

To enhance the need to stick with the rules, we ran subjects under two between-subjects conditions. For one group, the criterion was fairly easy to achieve. For the second group, the criterion was actually impossible to achieve. Thus, for this second group, participants had to work hard to optimize performance, although they would never actually exceed the performance criterion. To date, we have run this experiment only with a gains reward structure in which participants get points for correct answers and get no points for incorrect answers (Maddox, Baldwin & Markman, in press).

The results of this study are consistent with the predictions of regulatory fit. Participants do about equally well when the performance criterion is fairly easy to achieve. However, when the criterion is unattainable participants with a promotion focus (who have a regulatory fit) are significantly less accurate than are those with a prevention focus (who have a regulatory mismatch). When we fit models to participants' data, we find that there is more variability in the decision criterion for people with a promotion focus than for people with a prevention focus. This finding suggests that those with a promotion focus are trying a variety of different rules, while those with a prevention focus are sticking with a single rule and trying to refine it. Thus this pattern of data is also consistent with the proposal that a regulatory fit engages explicit processing more strongly than does a regulatory mismatch.

Converging evidence for this point comes from a comparison of learning rule-based and information-integration categories (Markman *et al.*, 2006). We performed a new study using a somewhat different manipulation of motivation than we used previously. In this study, in order to connect with research on 'choking under pressure' (e.g. Beilock & Carr, 2005; Beilock *et al.*, 2004; Gray, 2004; Masters, 1992), we created a social manipulation that creates a prevention focus and compared that to a control condition with no motivational manipulation. For this social manipulation, subjects are told that they and a partner are both performing the task and that if both of them exceed the performance criterion then both will receive a $6 monetary bonus. Furthermore, they are told that their partner has already performed the task and has exceeded the criterion. Thus the onus is on them to exceed the criterion as well. This manipulation creates a prevention focus, because participants typically perceive that their partner has achieved the bonus, and it is theirs to lose. This regulatory focus contrasts with the reward structure for the task, in which people receive positive points on each trial. Thus participants in the pressure condition have a regulatory mismatch. In contrast, the participants in the control condition are just told to 'do their best', and so they have a mild promotion focus that creates a regulatory fit with the gains reward structure of the task. Thus we expect the participants under pressure to have relatively less influence of explicit processes than participants with no pressure.

Participants are then given either a simple rule-based or information-integration category structure to learn. The rule-based task involves focusing on one of two stimulus dimensions. The information-integration task involves a conjunction of two dimensions that is not verbalizable. We expect that the control condition will be more likely to promote explicit processing because it leads to a regulatory fit, whereas the pressure condition leads to a regulatory mismatch. Conditions that promote explicit processing will yield relatively good performance on the rule-based task but relatively poor performance on the information-integration task, where the attempt to form rules will interfere with information-integration learning.

Consistent with our expectations, there was a reliable interaction between the category structure and the motivational state of the participants. When learning the rule-based categories, participants' performance was significantly worse when they were under pressure than when they were not. Furthermore, the data from participants in the low-pressure control condition were more likely to be fit by a rule-based model than were the data from participants in the pressure condition. These results reflect that the regulatory mismatch induced by the pressure manipulation impaired rule-based learning. In contrast, when learning the information-integration categories, participants' performance was significantly better when they were under pressure than when they were not. In addition, data from participants in the high-pressure condition were more likely to be fit by a procedural-based learning model than were data from participants in the low pressure control condition. This result reflects that the regulatory mismatch was advantageous in this situation, because participants were less likely to form rules in this case.

Taken together, the data reviewed in this section suggest that regulatory fit promotes explicit processing. Participants with a regulatory fit are more likely to use rule-based processes than are participants with a regulatory mismatch. When the task being performed requires learning complex rules, then a regulatory fit leads to better performance than does a regulatory mismatch. In contrast, when rule-based learning impairs performance, then participants perform more poorly when they have a regulatory fit than when they have a regulatory mismatch. Before we look at the broader implications of this view, we examine the influence of regulatory fit in another domain in order to assess the generality of the phenomena presented here.

Regulatory Fit and Choice

So far we have focused on the influence of regulatory focus and reward structure on concept learning. However, we are arguing that participants should be more likely to engage explicit processes when there is a regulatory fit than when there is a mismatch in general. Thus it would be useful to demonstrate another influence of regulatory fit. Recently we have begun to explore motivational factors in choice, and we present the results of a pilot study here.

We ran a group of thirty-eight subjects on a variant of the Iowa Gambling task (Bechara *et al*., 1994), a decision-making task that has been used to examine how people come to associate good and bad valence to choice options. In our version of the task, participants are shown two decks of cards on a computer screen. They are told that they can select cards from the decks and that the cards will have point totals on them. For half of the subjects, the point totals are positive and for the other half, the point totals are negative. For those given decks with positive point totals, their task is to draw eighty cards from the decks in a way that allows them to exceed a criterion point total to reach a bonus. For those given decks with negative point totals, their task is to select the eighty cards in a way that allows them to keep their point total above the criterion point total in order to reach a bonus. Subjects are shown the point total on the card after each draw.

Regulatory focus is manipulated in this study as well. The promotion focus involves the opportunity for subjects to get a raffle ticket for an entry to win $50 if they exceed the bonus criterion. In the prevention focus, subjects are given a raffle ticket for the draw and are allowed to keep it if their point total exceeds the criterion at the end of the study.

The two decks are constructed so that the initial impression of the decks is not consistent with their long-run value. The first few cards in one deck have high positive point totals (or low negative point totals), but the remaining cards have lower positive point totals (or higher negative point totals). We call this deck the 'bad' deck, because choosing it for the entire study will not allow the subject to reach the bonus criterion. The other deck has the opposite structure, and so it creates a bad impression at first, but ultimately subjects need to draw primarily from this deck to achieve the criterion. We refer to this deck as the 'good' deck. Thus, in order to succeed in this task, subjects need to recognize that the deck that looked good initially is in fact the bad deck, and that the deck that looked bad initially is in fact good. We hypothesized that succeeding in this task quickly would require explicit monitoring of performance, and so we expected that people would perform better if they had a regulatory fit than if they had a regulatory mismatch. In this study, a regulatory fit involves either a promotion focus and decks with positive point totals, or a prevention focus and decks with negative point totals.

The data support this hypothesis. Subjects given the decks with gains obtained significantly more points on average when they had a promotion focus ($M = 446$) than when they had a prevention focus ($M = 422$), $F(1,18) = 6.05$, $p < 0.05$. In contrast, subjects given the decks with losses showed the opposite pattern. In this case, subjects with a prevention focus lost fewer points on average ($M = -419$) than did subjects with a promotion focus ($M = -444$), $F(1,16) = 7.16$, $p < 0.05$. Thus participants with a regulatory fit performed better than did subjects with a regulatory mismatch. Ongoing research is exploring this phenomenon in more detail. In particular, we are examining the strategies people use in this task and people's ability to use these strategies flexibly.

These data allow us to extend our approach beyond simple perceptual learning. The decision-making task we gave people here required explicit monitoring of the items to recognize when an initially good item turned bad and when an initially bad item turned good. People were better able to recognize this shift when they had a regulatory fit than when they had a regulatory mismatch, suggesting greater involvement of explicit processing in this task.

Conclusions and Future Directions

Understanding the role of conscious processing in cognitive processing will be a difficult task, because normal cognition involves a mix of explicit and implicit processes. We believe that the research on the motivation-cognition interface described here in concept learning and other domains presents an interesting opportunity to help us learn more about the contributions of implicit and explicit processes in a variety of tasks. Regulatory fit appears to turn up the gain on explicit processes, while regulatory mismatch appears to turn down this gain. This method, then, provides us with a way of affecting the amount of conscious processing involved in task performance.

There are many techniques for trying to influence the contribution of explicit processing to cognitive processing, though we believe the manipulation of regulatory focus has advantages over all of them. For example, psychologists have long used dual-task paradigms to engage explicit resources in processing (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). While we have learned much about cognitive processing from dual-task studies, they place subjects in an unnatural situation and they often require significant training. Furthermore, performance in the tasks trades off depending on the degree of effort subjects place on the two tasks.

Other research has manipulated anxiety as a way of dampening available working-memory resources (e.g. Tohill & Holyoak, 2000). This manipulation is also expected to decrease the involvement of explicit processing in a task. In our view, manipulations of anxiety are a subcomponent of the framework described here. Anxiety is a state that is associated with avoidance goals (Higgins, 1987). People are anxious in situations in which they are attempting to avoid a potential negative outcome. There are two potential difficulties with research using anxiety to manipulate the degree of explicit processing in a task. First, this research generally attributes the effects of anxiety manipulations to anxiety rather than to the regulatory mismatch caused by activating a prevention focus in a task that (typically) rewards good performance. Second, this research does not recognize that activation of a prevention focus can actually lead to greater involvement of explicit processes when the task itself has losses.

The manipulations of regulatory fit described in this article also hold promise for future studies of brain imaging. Because the manipulation itself does not require any additional responses on the part of subjects, we can induce this manipulation and then examine task performance using imaging techniques like fMRI. Recent research by

Cunningham, Raye and Johnson (2005) found that manipulations of regulatory focus influence patterns of blood flow in evaluation tasks, suggesting that there is potential for these manipulations to further illuminate our understanding of brain regions involved in explicit processing.

Regulatory Fit and Consciousness

So far, we have suggested only that regulatory fit is associated with brain regions that are thought to promote conscious thought. In this section we give one speculation about why a regulatory fit would lead to greater conscious processing than a regulatory mismatch. Promotion and prevention foci are expectations about the projected state of the world. A promotion focus prepares an individual for a world in which there are potential gains and nongains in the environment. Likewise, a prevention focus prepares an individual for a world in which there are potential losses and nonlosses. When the reward structure of the environment matches individuals' expectations, then they should bring their full cognitive resources to bear on problems to be solved in that environment. However, when the reward structure mismatches individuals' expectations, then a reasonable initial response is to engage fast-acting (and probably unconscious) cognitive strategies until the environment can be better understood.

This possibility is sensible, because in most situations the regulatory focus is aligned with the task being performed, and so the reward structure of that task often helps to create the active regulatory focus. In the world in which the human cognitive system evolved, mismatches probably occurred when individuals had mistaken expectations about the nature of a task or environment. In cases in which expectations have been violated, it is important to be reactive to stimuli in the environment. However, the modern world contains a number of socially-defined incentive systems for which our motivational apparatus may not be optimized. Thus it is important to have a better understanding of what situations do and do not engage conscious processing in order to create social scaffolding that engages appropriate motivational states for the tasks we ask people to perform.

Future Research

In any study of cognitive processing there is a tension between gaining control of the stimuli and task so that it can be modelled accurately and the exploration of tasks that have the complexity of those pursued by people outside the laboratory setting. So far we have focused primarily on simple concept learning tasks in which we have fine control over both the stimuli and the processes people bring to bear on the task. This control has been useful in allowing us to discover the complex interaction underlying regulatory fit. Now that the structure of this interaction has become clear, however, we wish to broaden our focus to explore a wider range of cognitive tasks to better understand the interplay of explicit and implicit processes.

One important line of research that we plan to continue is the study of performance under pressure. The existing literature on pressure suggests that under some circumstances expert performance is hurt by using explicit processes when a highly-learned skill should be carried out implicitly (Gray, 2004; Masters, 1992). In contrast, other research suggests that performance may be harmed under pressure by constricting the availability of conscious resources (Beilock & Carr, 2005; Beilock *et al.*, 2004). The research described above suggests that the regulatory fit framework presented here will be useful for exploring this situation in more detail.

Other social phenomena may also be related to the regulatory fit framework described. For example, research on stereotype threat suggests that people's performance in a cognitive task may be impaired if they are a member of a group that is stereotypically thought to be bad at a task and if that stereotype is activated during task performance (e.g. Steele, 1997; Steele & Aronson, 1995). Most research on stereotype threat, however, involves tasks for which people are rewarded for their performance during the task. Thus it is possible that stereotype threat creates a regulatory mismatch, which decreases the involvement of conscious processing used by subjects under threat. Thus it is possible that the effects of stereotype threat may be reversed in tasks with a negative reward structure.

Finally, as cognitive psychologists, we know that there is a wide array of individual differences in task performance that becomes 'noise' in our data. Much of this noise may arise from personality characteristics that affect the chronic regulatory focus of our participants. For example, anxiety may be related to a prevention focus in participants (Higgins, 1987). Furthermore, behavioural inhibition and activation may be related to the motivational states participants bring to studies (Pickering & Gray, 2001). By better understanding the influence of motivational state on the degree of conscious processing in cognitive tasks, we may be better able to control these sources of variability in our experiments. Ultimately, this control will provide us with a better understanding of the interplay of implicit and explicit processes in normal cognitive performance.

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