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Regulatory fit effects on stimulus identification

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Abstract This article examines the effects of a fit between a person's global regulatory focus and the local task reward structure on perceptual processing and judgment. On each trial, participants were presented with one of two briefly presented stimuli and were asked to identify it. Participants were placed in a promotion focus (a situationally induced sensitivity to gains) or a prevention focus (a situationally induced sensitivity to losses) and were asked to maximize gains or minimize losses. An asymmetric payoff ratio biased the overall reward toward one identification response over the other. Two experiments tested the role of regulatory fit when internal familiarity and perceptual sensitivity were low or high. When familiarity and sensitivity were low, participants in a regulatory fit (promotion focus with gains or a prevention focus with losses) showed greater perceptual sensitivity but no response bias differences, relative to participants in a regulatory mismatch. When familiarity and sensitivity were high, participants in a regulatory fit showed a response bias toward the high-payoff stimulus but no differences in perceptual sensitivity. Speculations are offered on the neurobiological basis of this effect, as well as implications of this work for clinical disorders such as depression.

Keywords Motivation · Regulatory focus · Perception · Identification · Signal Detection

Motivation influences people's performance on an array of tasks ranging from complex learning to simple perceptual discrimination (Humphreys & Revelle, 1984). It is crucial to understand these influences, particularly on perceptual tasks, because considerable effort is spent trying to motivate such individuals as air traffic controllers and radiologists, whose job success depends on efficient and effective perceptual processing. Despite the importance of motivation both in laboratory studies and in the workplace, the effect of motivational manipulations such as incentives is still poorly understood (Brehm & Self, 1989; Locke & Latham, 2002; Maddox & Markman, 2010).

In this article, we extend previous work from our lab to focus on the effects of incentives on a perceptual discrimination task. As we will discuss, these perceptual discrimination tasks allow us to explore influences of motivation on both judgments and internal perceptual noise. We start with a review of the regulatory fit motivational framework that has driven our research. Then, we introduce the experimental procedure and present two experiments that explore the effects of motivational incentives on performance.

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The regulatory fit framework

Previous research from our lab suggested that the influence of an incentive on performance is best conceptualized as an interaction between the motivational state induced by the incentive versus the rewards or punishments provided by a task (Maddox, Baldwin, & Markman, 2006; Maddox, Markman, & Baldwin, 2007; Markman, Baldwin, & Maddox, 2005; Markman, Maddox, Worthy, & Baldwin, 2007; Worthy, Maddox, & Markman, 2007, 2008). This idea is related to Higgins's concept of a *regulatory fit* (Avnet & Higgins, 2003; Higgins, 1997; Higgins, 2000).

In this view, a situational incentive induces a *promotion focus* (when participants try to achieve a positive reward) or a *prevention focus* (when participants try to avoid a negative punishment). For example, when people are performing a task, they may have the opportunity to earn a ticket for a drawing to win $50 (promotion focus), or they may be given a ticket for the drawing when entering the lab and have to perform well or lose the ticket (prevention focus).

Tasks also have local incentives. Points can be obtained on each trial (*gains*) with the goal of maximizing points, or they can be lost on each trial (losses) with the goal of minimizing losses. We believe that both gain maximization and loss minimization are ecologically valid constructs. For gains, consider a seashell collector who finds many good seashells if a good part of the beach is chosen, but only a few seashells if a bad part of the beach is chosen. Regardless of success, the number of seashells collected is always increasing. For losses, consider a delivery driver with a limited amount of gasoline for his many routes. If a good route is chosen, a smaller amount of gas will be consumed, but if a poor route is chosen, a larger amount of gas will be consumed. Regardless of success, the amount of gasoline is always decreasing.

A regulatory fit occurs when there is a global approach incentive and the task involves a local gains incentive, or when there is a global avoidance incentive with a local losses incentive (promotion–gains and prevention–losses). The other states create a regulatory mismatch (promotion–losses and prevention–gains; see Table 1). An example of a promotion–gains regulatory fit would be a seashell collector who is trying to collect enough seashells to gain an entry into a local seashell competition. An example of a prevention–loss regulatory mismatch would be a delivery driver who was trying to avoid being fired by trying not to running out of gas on his route. In our work, we find an interaction between global situational incentives and local task reward incentives on performance.

It is critical to note that this interaction of global and local incentives further interacts with properties of the task at hand. For example, Grimm, Markman, Maddox, and Baldwin (2008) observed a three-way interaction of global incentives, local incentives, and whether flexible strategies facilitate or hinder performance in a classification task. In other words, the interaction of global and local incentives resulted in either a fit interaction or a mismatch interaction, which additionally interacted with task-processing requirements. Those in a regulatory fit interaction demonstrated better classification performance when the task required a flexible, rule-based strategy. Conversely, those in a regulatory mismatch interaction demonstrated better performance when the task required a more incremental, implicit strategy. This three-way interaction eludes simple main-effect explanations and signifies that a regulatory fit between global and local incentives does not universally lead to better performance, regardless of task properties.

Studying perceptual identification

This article applies the three-factor motivation–cognition framework to a perceptual identification task in two experiments. Previous research suggested that a regulatory fit between global and local incentives has consequences for higher-level decision making. Markman et al. (2005) demonstrated that regulatory fit leads to differences in the classification of items drawn from continuous and overlapping category distributions. In that study, the decision criterion needed to maximize reward differed from that required to maximize classification accuracy, because rewards associated with one category were three times greater than those associated with the other category (see Green & Swets, 1966; Maddox, 2002, for details). People have a natural tendency to maximize accuracy, so flexi/bility is required in order to abandon the decision criterion that maximizes accuracy for the one that maximizes reward (Maddox, 2002; Maddox & Bohil, 1998; Maddox & Dodd, 2001). Given this setup, participants in a regulatory fit exhibited flexibility by shifting their decision criterion away from the accuracy-maximizing criterion and toward the reward-maximizing criterion.

We build on this established higher-level response bias effect and investigate lower-level processing using tools offered by signal detection theory. Detection and identification of briefly presented stimuli is a hallmark of the sensory and perceptual systems, forming the bases for

Table 1 Regulatory fit framework

	Local Task Reward Structure	
Global Regulatory Focus	Gains	Losses
Promotion focus	Fit	Mismatch
Prevention focus	Mismatch	Fit

much higher-level cognition (Wilson, 2002). The studies outlined above all used classification tasks in which large numbers of physically unique stimuli were each sampled from normally distributed categories, and the participants' task was to classify each stimulus into its associated category. These paradigms have their roots in early "external noise" distribution studies, whose aim was to make the "noise" characteristics observable (i.e., external) so that decision processes could be studied (Healy & Kubovy, 1981; Lee & Zentall, 1966). In the present investigation, we returned to the more basic signal detection/perceptual identification paradigm, in which only two unique stimuli are relevant and the participant is asked to identify which is presented on each trial. The stimuli are highly perceptually confusable and are presented for short durations, significantly increasing the influence of internal noise. To our knowledge, this represents the first study to examine the impact of regulatory fit on perceptual and decisional processes in stimulus identification.

To study stimulus identification with internal noise characteristics, we introduced a critical change from our prior work. Markman et al. (2005) examined category learning with simple unidimensional stimuli. Each category contained a large number of unique stimuli, with each stimulus being sampled from a univariate normal category distribution (i.e., with external noise). Critically, each stimulus was presented in a high-contrast, response-terminated display. Thus, while perceptual noise was negligible, noise was introduced into the process by utilizing highly overlapping category distributions. In the stimulus identification paradigm used in this article, only two stimuli are relevant, but "noise" is introduced by using highly confusable stimuli and short display durations. Thus, the main source of noise is perceptual and comes from the internal representation of each stimulus. Because there are two stimuli and two responses in stimulus identification, performance in the task can be quantified by calculating the probability of a "hit" and a "miss" for each stimulus. Specifically, for Stimulus_1, there are Hits_1 and Misses_1, and for Stimulus_2, there are Hits_2 and Misses_2. These labels are equivalent to the traditional signal detection theory measures of hits (Hits_1), misses (Misses_1), correct rejections (Hits_2), and false alarms (Misses_2) taken relative to Stimulus_1 as the signal and Stimulus_2 as noise.

These quantities are used to calculate two fundamental measures of stimulus identification performance: perceptual sensitivity and response bias (see Fig. 1). *Perceptual sensitivity* is a measure of the ability to discriminate between the two stimuli (i.e., the distance between the perceptual distributions of the stimuli along an evidence *x*-axis). *Response bias* is a measure of the tendency to endorse or select one response choice over the other. Sensitivity is usually influenced by stimulus characteristics such as stimulus discriminability and exposure duration, and response bias is influenced by the rewards and/or costs associated with correct and incorrect responses for each stimulus (McCarthy & Davison, 1979; Wickens, 2001; but see Balakrishnan, 1999). A person's performance in a stimulus identification task can vary along these two independent measures of performance (e.g., high perceptual sensitivity and moderate response bias, low perceptual sensitivity and moderate response bias).

Stimulus characteristics can drive both empirical perceptual sensitivity and response bias. Typically, increased discriminability leads to increased empirical sensitivity. Response bias can be manipulated, for example, with the instantiation of an asymmetric local reward structure. In a symmetric payoff situation, equal rewards are given for Hits_1 and Hits_2, and equal rewards are also given for Misses_1 and Misses_2. The optimal response bias (β) is computed as follows:

$$\beta = \frac{(Hits_1 - Misses_1)P(Stimulus_1)}{(Hits_2 - Misses_2)P(Stimulus_2)}, \tag{1}$$

where $Hits_i$ and $Misses_i$ refer to the reward given for either a hit or miss response to Stimulus_i and $P(\text{Stimulus}_i)$ is the proportion of times Stimulus_i is shown (i.e., base rate).

Assuming equal base rates, in a symmetric payoff situation, the reward values in Eq. 1 are equal for both stimuli. Under these conditions, $\beta=1$, as shown below:

$$\beta_{Symmetric} = \frac{(200-100)(.5)}{(200-100)(.5)} = \frac{100}{100}1. \tag{2}$$

The accuracy-maximizing criterion, given by the ratio of the base rates, is also 1. Therefore, in a symmetric payoff situation, the accuracy maximizing criterion is the same as the reward-maximizing criterion.

Again assuming equal base rates, in an asymmetric payoff situation, the reward values are unequal. For

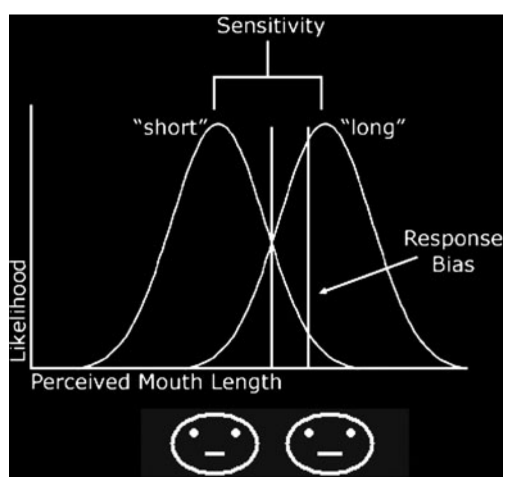

Fig. 1 Stimulus identification properties of a simple identification task

example, in the present tasks, $Hits_1$ = 400, $Hits_2$ = 200, while $Misses_1$ = $Misses_2$ = 100. Under these conditions, the optimal decision criterion = 3, as described below:

$$\beta_{Asymmetric} = \frac{(400-100)(.5)}{(200-100)(.5)} = \frac{150}{50} = 3 \qquad (3)$$

The accuracy-maximizing decision criterion is 1. Thus, the reward-maximizing criterion differs from the accuracy-maximizing criterion, requiring participants to abandon their natural tendency toward accuracy maximization in favor of reward maximization.

This β value was chosen as a starting point based on our prior research. The local reward structures of the present tasks all had β = 3. However, there were two between-participants conditions that differed in the specific reward values. In the *gains* condition, participants gained more points for correct responses than for incorrect responses while approaching a positive bonus point criterion. In the *losses* condition, participants lost fewer points for a correct response than for incorrect responses while avoiding a negative bonus point criterion (see Fig. 2). In both scenarios, more points were given for correct responses, but importantly, more points were given for a response to one stimulus relative to the other. Because of the equal base rates and the use of two discrete stimuli, both high accuracy and a shifted response criterion would result in high task performance (i.e., more gains or fewer losses). For this reason, it was crucial for overall discriminability to be low, such that perfect accuracy was unlikely.

There are three ways that regulatory fit might affect performance in this internal-noise experiment. First, regulatory fit might affect the location of the decision criterion, as in prior work with stimuli with external noise. In previous work, we found that a regulatory fit increased participants' willingness to abandon accuracy maximization in the interest of maximizing reward, leading to a shift in the decision criterion in a two-category classification task (Markman et al., 2005). Extending this effect to stimulus identification would suggest that the regulatory fit interaction previously observed with suprathreshold, highly discriminable stimuli and response-terminated displays extends to internal-noise scenarios with two stimuli. Second, an intriguing possibility is that regulatory fit increases perceptual sensitivity; there is some neuropsychological evidence to suggest that this might be the case. For example, increased dopamine in frontal areas (that might be associated with a regulatory fit; Maddox et al., 2006) could increase the signal-to-noise ratio associated with projections from sensory representation areas into prefrontal cortex (Ashby & Casale, 2003; Ashby, Ell, Valentin, & Casale, 2005). This is an exciting possibility because it suggests that the interaction of global and local

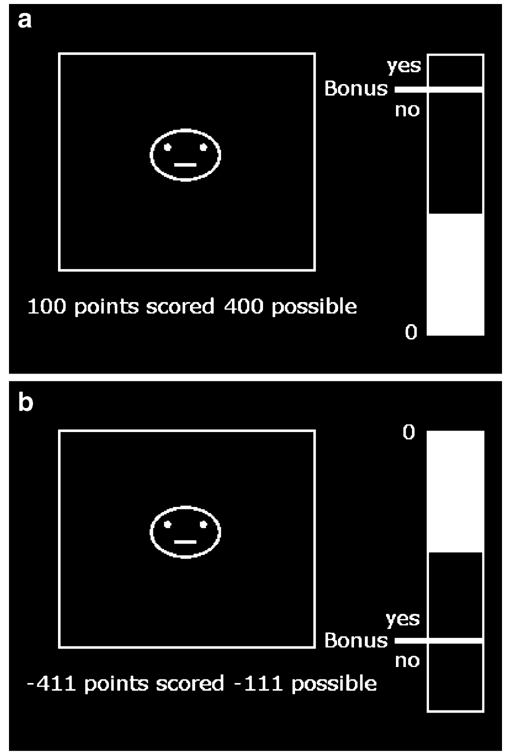

Fig. 2 (**a**) Sample display from the gains condition. (**b**) Sample display from the losses condition

incentives can affect low-level perceptual processing. The neuropsychological basis for this possibility is discussed in more detail in the General Discussion. Lastly, regulatory fit might affect both criterion placement and perceptual sensitivity. Based on our previous work (Markman et al., 2005), our a priori prediction is that regulatory fit will affect the placement of the decision criterion. Even so, the perceptual sensitivity hypothesis is compelling.

Overview of the present experiments

Experiment 1 used a perceptual identification task with two highly confusable stimuli, short exposure duration, and limited training. Global regulatory focus (promotion or prevention) and local task reward structure (gains or losses) were manipulated between participants. From prior work, we expected global regulatory focus and local reward structure to interact such that those in a regulatory fit (promotion–gains and prevention–losses) would demonstrate a response bias shift away from the accuracy-maximizing decision criterion and toward the rewards-maximizing criterion. This prediction was based on a similar finding of the role of regulatory fit in the placement of the decision criterion in category learning (Markman et al., 2005). To anticipate the results, we were surprised to find that those in a regulatory fit demonstrated increased perceptual sensitivity relative to those in a regulatory mismatch (promotion–losses and prevention–gains).

In Experiment 2, we attempted to bridge the gap between the procedures associated with our stimulus identification task in Experiment 1 and those used in our prior work (Markman et al., 2005). The idea was to distinguish the lower-level consequences of regulatory fit observed with novice participants performing a *perceptually* difficult stimulus identification task (Experiment 1) from the higher-level consequences common in our prior work (Maddox et al., 2006, 2007; Markman et al., 2005, 2007; Worthy et al., 2007) by modifying the procedure used in Experiment 1. During pretraining, we provided participants with extensive experience with the task and adjusted the stimulus presentation time so they could reliably achieve 70% accuracy. There was no global regulatory focus or local reward structure manipulation during pretraining, resulting in a symmetric feedback scenario in which the optimal β = 1 (see Eq. 2). Once performance stabilized (see the details for Experiment 2), we introduced the global regulatory focus (promotion vs. prevention) and local reward structure (gains vs. losses) manipulations and modified the payoff matrix so that now optimal β = 3. We hypothesized that, under these conditions, a regulatory fit would increase flexibility in such a way that participants would shift their decision criterion away from the accuracy-maximizing criterion and toward the reward-maximizing criterion. To anticipate, participants in a regulatory fit did demonstrate a shift toward the reward-maximizing decision criterion. In the General Discussion, we speculate on the neurobiological underpinning of these effects and discuss implications of this work for recent work in clinical populations, such as patients with depression.

Experiment 1

In Experiment 1, participants were given a situational promotion or prevention focus and were asked to complete several hundred trials in which they identified one of two schematic faces that differed only in the width of the mouth (see Pizzagalli, Jahn, & O'Shea, 2005, for a similar task). On each trial, one of the two (randomly selected) stimuli was presented for 100 ms, and the participant decided whether the mouth was "short" (Stimulus_1) or "long" (Stimulus_2). Participants in the gains condition received points for each response, but received more points for correct responses (Hits_1 and Hits_2) than for incorrect responses (Misses_1 and Misses_2; see Fig. 2a). Participants in the losses condition lost points for each response, but they lost fewer points for correct than for incorrect responses (Fig. 2b). Importantly, the payoff ratio was asymmetric, with Hits_1 yielding a better payoff than Hits_2. The exact payoffs are displayed in Table 2. In both conditions, a higher score was more desirable than a lower score. Importantly, these payoffs were designed to yield the same optimal decision criterion for gains and losses (β = 3; see Eq. 1).

Method

Seventy-six participants from the University of Texas community completed the study, with 21, 20, 18, and 17, respectively, in the promotion–gains, promotion–losses, prevention–gains, and prevention–losses conditions. Participants were either paid $6 for their time or given course credit. In addition, they were all given the opportunity to receive entries into a drawing for a one-in-ten chance to win $50. The data from 12 participants (3 in promotion–gains, 3 in promotion–losses, 4 in prevention–gains, and 2 in prevention–losses) were eliminated from analysis due to perseverative responding or to a majority of trials with response times below 200 ms, possibly due to frustration. Testing occurred individually in a well-lit room.

The stimuli were two schematic faces that differed only in the width of the mouth, with the short mouth measuring 36 pixels and the long mouth measuring 38 pixels. Both faces shared an outer oval shape and the position of two dots to represent eyes (see the examples in Fig. 2). On each trial, one (randomly selected) stimulus was presented for 100 ms, followed by a 500-ms Gabor patch mask. The participant pressed the "short" or "long" mouth key and was informed of the number of points earned or lost. A point meter incremented or decremented following each response. The asymmetric payoff matrix (see Table 2) created a reward dichotomy between Stimulus_1 and Stimulus_2 and was necessary for measuring task-appropriate changes in response bias (see Eq. 1).

Participants completed a 40-trial practice phase in which they received corrective feedback with no payoff structure. This was followed by three 100-trial blocks of stimulus identification. Before the first block, the global regulatory focus manipulation was introduced. Promotion focus

Table 2 Payoff matrices and performance criterion for the between-participants manipulation of gains and losses

	Experiment 1		Experiment 2	
	Gain	Loss	Gain	Loss
Hit_1(Higher reward)	400	–111	4	–1
Hit_2 (Lower reward)	200	–311	2	–3
Miss_1	100	–411	1	–4
Miss_2	100	–411	1	–4
Performance criterion	22,400	–28,600	130	–120

participants were told that in each block, if their performance exceeded the criterion, they would receive one raffle ticket. Prevention focus participants were given three raffle tickets at the start of the experiment. They were told that they would lose a raffle ticket in each block of trials in which they lost too many points.

After the training phase, the payoff structure was explained to the participant. Gains participants were told that they needed to gain enough points to exceed the criterion to obtain or keep the raffle ticket. Losses participants were told that they needed to minimize their losses to stay above the criterion to obtain or keep the raffle ticket. The performance criterion for two payoff conditions was set at 68% of the difference between the highest and lowest possible point total for a block of trials, and is displayed in Table 2. Points were reset to zero at the beginning of each block.

Results

Sensitivity and response bias are important measures in stimulus identification tasks. Sensitivity is related to accuracy and is a measure of a participant's ability to discriminate between the two stimuli in the task. Response bias is a measure of the tendency of a participant to favor one response over the other. Here, we used empirical measures of sensitivity (log *d*; Eq. 4) and response bias (log *b*; Eq. 5). These measures are well behaved at various levels of accuracy (McCarthy & Davison, 1979; Tripp & Alsop, 1999). They were chosen in lieu of *d*-prime and *Beta* because *Beta* is most interpretable when a single level of discrimination is imposed on a stimulus space with external noise or when a small range of empirical sensitivities are recovered from an identification task with internal noise. While both paradigms are parametric, in that *d*-prime and *Beta* assume a normal distribution and log *d* and log *b* assume a logistic distribution, we found log *b* to be most resilient to a range of empirical sensitivities and less distorted by the level of discriminability. Most applications of either method assume equal variances. We make this same assumption, but address its implications in the General Discussion.

For log *d*, positive values represent a tendency to correctly identify both Stimulus_1 and Stimulus_2. For log *b*, positive values represent a tendency to identify stimuli as Stimulus_1 (the high-payoff stimulus) rather than Stimulus_2 (the low-payoff stimulus). Thus, larger values are indicative of larger shifts toward the reward-maximizing criterion.

$$\log d = 0.5^* \log\left(\frac{Hits_1{}^*Hits_2}{Misses_1{}^*Misses_2}\right) \tag{4}$$

$$\log b = 0.5^* \log\left(\frac{Hits_1{}^*Misses_1}{Hits_2{}^*Misses_2}\right) \tag{5}$$

Perceptual sensitivity (log d) The stimulus identification sensitivity (log *d*) values are displayed in Fig. 3a and were subjected to a 2 (focus: promotion, prevention) x 2 (local reward structure: gains, losses) × 3 (block) ANOVA. Global regulatory focus interacted with local reward structure, $F(1, 60) = 9.86$, $p = .003$, $\varepsilon^2 = .14$. Pairwise *t* tests suggested higher sensitivity for participants in the promotion–gains condition (log $d = 0.91$) relative to those in the promotion–losses condition (log $d = 0.64$), $t(33) = 2.20$, $p = .035$, and higher sensitivity for participants in the prevention–losses condition (log $d = 1.12$) relative to those in the prevention–gains condition (log $d = 0.82$), $t(27) = 2.26$, $p = .016$. There was also no significant difference between the promotion–gains and prevention–losses conditions, $t(31) = 1.69$, $p = .10$, nor between the promotion–losses and prevention–gains conditions, $t(29) = 1.36$, $p = .19$. Proportion correct (i.e., accuracy) is highly correlated with log *d*, although not by a linear transformation. Proportion correct analyses led to the same results.

Stimulus identification decision criterion (log b) The stimulus identification decision criterion (log *b*) values are displayed in Fig. 3b and were subjected to a 2 × 2 × 3 ANOVA. The main effect of local reward structure was nearly significant, $F(1, 60) = 3.96$, $p = .051$, $\varepsilon^2 = .062$, and suggested that participants in the gains condition showed a larger shift toward the reward-maximizing decision criterion relative to those in the losses condition. Because we expected the regulatory fit interaction to affect response bias, we compared the regulatory fit groups versus the regulatory mismatch groups for both sensitivity and bias. The difference was significant for log *d*, $t(62) = 3.08$, $p = .003$, $d = .73$, mean difference 95% confidence interval (CI) [–0.47, –0.10], but not for log *b*, $t(62) = -0.50$, $p = .62$, $d = -.17$, mean difference 95% CI [–0.13, 0.27].

Effects of learning Although block did not interact significantly with global regulatory focus or local task reward structure, an examination of Fig. 3 suggests a consistent trend whereby the effects of regulatory fit (i.e., better performance for promotion–gains relative to promotion–losses and prevention–losses relative to prevention–gains) tended to be largest in the first block of trials and diminished over blocks. In fact, performance for regulatory fit participants was fairly stable across the three blocks, whereas there was a general tendency for performance of regulatory mismatch participants to start poor and gradually improve. The interaction of global regulatory focus and local reward structure was significant for log *d* in Blocks 1 and 2 but was nonsignificant in Block 3—$F(1, 60) = 14.67$, $p < .001$, $\varepsilon^2 = .196$ in Block 1; $F(1, 60) = 5.45$, $p = .023$, $\varepsilon^2 = .083$ in Block 2; and $F(1, 60) = 2.21$, $p = .14$, $\varepsilon^2 = .036$ in Block 3. Thus, it does not appear that a regulatory

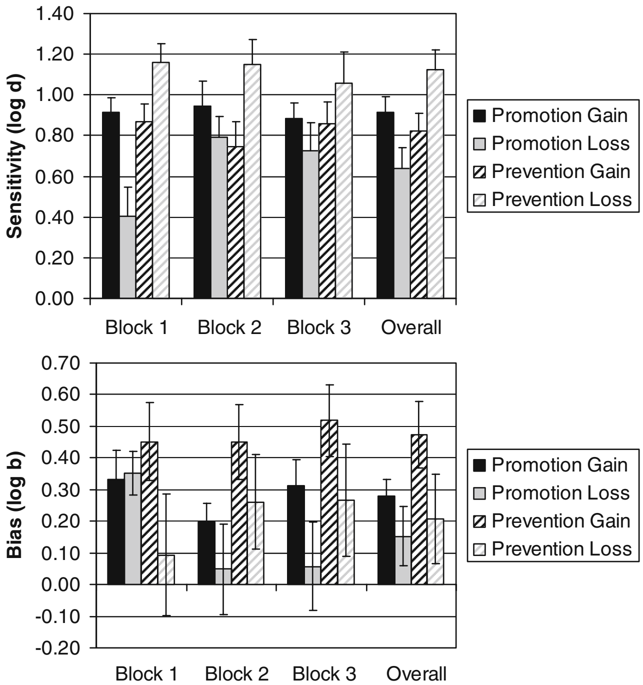

Fig. 3 Performance measures from Experiment 1 for each block and collapsed across blocks. Error bars represent standard errors

fit leads to higher asymptotic levels of performance, but rather leads to faster initial learning.

In summary, in a stimulus identification task with internal noise and a short exposure duration, we found an interaction of global incentives (regulatory focus) and local incentives (local task reward structure), such that a regulatory fit interaction leads to higher sensitivity but not to a decision criterion shift. Although we predicted an effect of regulatory fit on response bias based on previous work, there was some reason to expect a regulatory fit effect on sensitivity. In Experiment 2, we tested whether decreased perceptual noise would lead to the regulatory fit effect on response bias that we have shown in previous work.

Experiment 2

The novel results from Experiment 1 suggest that the interaction of global and local incentives has consequences for low-level perceptual processing. Our prior work with regulatory fit and higher-level decision making revealed motivational consequences for higher-level processes such as decision criterion placement in a classification task. To determine the juncture between regulatory fit effects on decision criterion placement in a classification task and perceptual sensitivity in a stimulus identification task, we examined the possibility that increased training and familiarity with the stimulus identification task might allow participants in a regulatory fit to develop a response bias toward the high-reward stimulus. To this end, we modified Experiment 1 to promote increased overall accuracy and perceptual sensitivity by increasing trial-by-trial exposure duration and offering increased familiarity through training. We predicted that increased training and familiarity with the stimulus identification task would lead those in the regulatory fit condition to shift bias toward the higher-reward response.

Method

Ninety-one participants from the University of Texas community completed the study with 24, 19, 26, and 22 in the promotion–gains, promotion–losses, prevention–gains, and prevention–losses conditions, respectively. In this analysis, we were only interested in the stimulus identification performance of those who successfully achieved the bonus criterion in at least one of the motivation blocks.[1] This led to the exclusion of 4 participants from promotion–gains, 4 from promotion–losses, 7 from prevention–gains, and 5 from prevention–losses.

To achieve higher overall accuracy, we introduced a titration phase consisting of four blocks of 50 stimulus identification trials with corrective feedback. These blocks occurred before the regulatory focus manipulation was instantiated, and they had a symmetric local task reward structure in that no points were given as feedback. After each titration block, the stimulus presentation time was adjusted based on Eq. 6:

$$newtime = \frac{oldtime}{accuracy} * 0.7, \tag{6}$$

where *oldtime* refers to the stimulus presentation time carried over from the previous trial, *accuracy* refers to cumulative accuracy of the participant on the previous trials, and the target accuracy rate is set to .7. The initial stimulus presentation time was set at 200 ms. This training procedure was effective, yielding a mean accuracy of 77% (SE = 0.01) at the end of the titration phase.

The stimuli in this study were gray 50 × 50 pixel patches at two levels of brightness. We abandoned the face paradigm because the gray patches gave us more control for a titration procedure. We found that even a 1-pixel change in mouth length had a drastic effect on accuracy that was too large for the aims of the titration procedure. On each trial, participants were instructed to classify a presented stimulus by pressing one of two response buttons. After the titration blocks, the motivational manipulation was instantiated as in Experiment 1.

[1] The same pattern of results reported below held for Experiment 1 when this same restriction was applied.

Participants engaged in three motivation blocks of 50 trials. As in Experiment 1, an asymmetric payoff matrix was constructed with an optimal decision criterion (β) of 3. See Table 2 for the payoff matrix used in Experiment 2. Since the higher accuracy would inevitably lead to more participants reaching the bonus point criterion, the criterion was raised to 80% of the maximum possible points minus the minimum possible points. Stimulus masks and response keys were the same as in Experiment 1. The proportion of those to achieve the bonus was such that there was a main effect of local reward structure, $F(1,\ 67) = 8.32$, $p = .005$, but no interaction of global regulatory focus and local reward structure.

Results

Perceptual sensitivity (log d) The stimulus identification sensitivity (log *d*) values are displayed in Fig. 4a and were subjected to a 2 × 2 × 3 ANOVA. The relative ease of the task in comparison to Experiment 1 led participants to greater sensitivity as the task proceeded. The main effect of block was significant, $F(1, 67) = 17.3$, $p<.001$, $\varepsilon^2 = .21$, as well as the main effect of local reward structure, $F(1, 67) = 9.1$, $p = .004$, $\varepsilon^2 = .12$. Importantly, and unlike the results from Experiment 1, there was no interaction of global regulatory focus and local reward structure. Analysis of the proportion correct data yielded the same pattern.

Stimulus identification decision criterion (log b) The stimulus identification decision criterion (log *b*) values are displayed in Fig. 4b and were also subjected to a 2 × 2 × 3 ANOVA. There was a significant interaction of global regulatory focus and local reward structure, $F(1,\ 67) = 4.8$, $p = .033$, $\varepsilon^2 = .07$. This interaction reflects the fact that participants in a regulatory fit were more strongly biased away from an accuracy-maximizing criterion and toward a higher-payoff reward-maximizing criterion (i.e., a response shift toward Stimulus_1) than those in a regulatory mismatch. Pairwise *t* tests suggested a shifted response bias for participants in the promotion–gains condition (log $b = 0.29$) relative to participants in the promotion–losses condition (log $b = 0.02$), $t(33) = 2.18$, $p = .037$, but only a directional nonsignificant difference for participants in the prevention–losses condition (log $b = 0.02$) relative to participants in the prevention–gains condition (log $b = 0.15$), $t(34) = 0.95$, $p = .35$. There was also no significant difference between the promotion–gains and prevention–losses conditions, $t(35) = 0.99$, $p = .33$, nor between the promotion–losses and prevention–gains conditions, $t(32) = 0.02$, $p = .98$. There were no significant main effects of global regulatory focus or local reward structure. Because we expected the regulatory fit interaction to affect sensitivity, we compared the regulatory fit groups versus the regulatory mismatch groups for both sensitivity and bias. The difference was significant for log *b*, $t(69) = 2.26$, $p = .03$, $d = .51$, mean difference 95% CI [–0.39, –0.02], but not for log *d*, $t(62) = 0.29$, $p = .77$, $d = .12$, mean difference 95% CI [–0.40, 0.24].

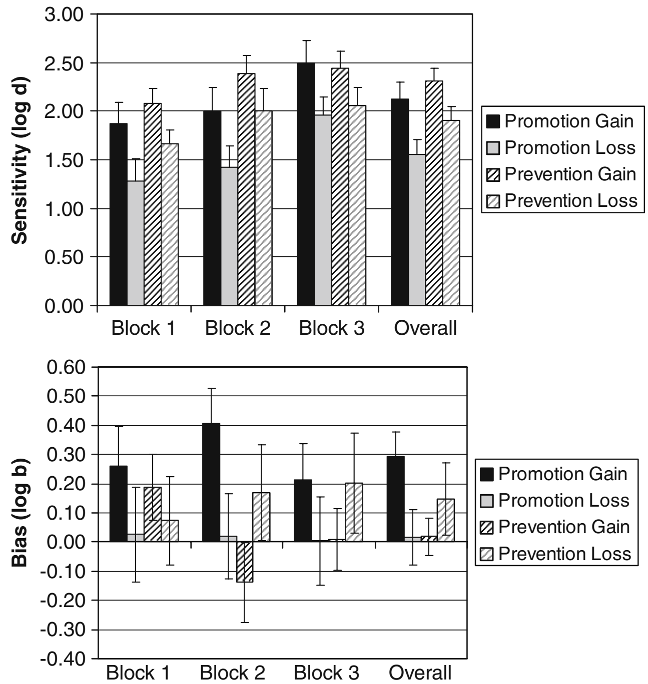

Fig. 4 Performance measures from Experiment 2 for each block and collapsed across blocks. Error bars represent standard errors

In summary, Experiment 2 featured a titration training procedure that led to decreased perceptual noise and a regulatory fit effect on response bias, as found in our previous work. This is in contrast to the regulatory fit effect on sensitivity found in Experiment 1, for which the internal perceptual representations were noisier. We discuss the significance of these results below.

General discussion

This article addresses the effect of incentives on performance using a simple stimulus identification task. Consistent with previous work, we found not only an interaction between the global situational incentive and the local task reward structure, but also the processing required by the task itself. This study goes beyond previous research, however, by demonstrating that a regulatory fit between the global regulatory focus and the local task reward structure affected performance differentially, depending on the level of internal perceptual noise. With higher internal perceptual noise, regulatory fit increased perceptual sensitivity (as measured by log *d* from signal detection theory and traditional measures of accuracy),[2] whereas with lower internal perceptual noise, regulatory fit affected response bias in that those in a regulatory fit were more likely to abandon their natural tendency toward accuracy maximization in favor of reward maximization, thus increasing their chance of obtaining or keeping the raffle ticket entry. The increased empirical discriminability in Experiment 2 resulted from the longer exposure duration on each trial and increased familiarity with the stimuli due to the increased training phase. This allowed participants to attend to the asymmetric reward characteristics of the task. With perceptual discriminability no longer a struggle for participants, response bias effects emerged for participants in the two regulatory fit conditions.

Our results do indicate that perceptual sensitivity is influenced by regulatory fit in situations of low perceptual discriminability, although it may be possible that perceptual sensitivity is also influenced in higher-discriminability situations, albeit to a smaller degree. It is also possible that the regulatory fit effect on sensitivity is larger early in learning, followed by the emergence of an effect on response bias later in learning, due to the fact that discriminability often increases through experience with stimuli

We must emphasize that these experiments (like our previous work) can be explained only by theories that postulate an interaction between the global regulatory focus, local reward structure, and task properties on performance. Theories that posit overall differences between global promotion and prevention focus (e.g., Crowe & Higgins, 1997; Higgins & Scholer, 2009) or local gains and losses only (e.g., Kahneman & Tversky, 1979) are not sufficient to account for the present results. Furthermore, although this was not manipulated in the present experiments, prior work demonstrated an additional tertiary interaction between regulatory fit and task demands. For example, the increased exploratory response pattern of those in a regulatory fit can hinder performance in tasks where an exploitative response pattern is optimal (Worthy et al., 2007, 2008). This tertiary interaction (Regulatory Focus x Local Reward Structure x Task Demands) attenuates engagement and/or attention hypotheses regarding regulatory fit. In summary, this pattern of results demonstrates that regulatory fit is not a universally beneficial psychological state, and further precludes the usefulness of theories that ignore the interactive properties of global and local incentives.

[2] Response bias was (nonsignificantly) shifted toward the higher-reward stimulus in the gains condition. This effect was not predicted by our framework, and Experiment 2 did not replicate this main effect, but future work should pay attention to potential main effects that may occur.

In Experiment 1, we predicted an effect of regulatory fit on response bias. Instead, we found an effect on perceptual sensitivity. Although it was initially surprising, an examination of the relevant neuroscience literature supports this finding. Neuroscience research has suggested that motivational state might influence sensitivity when perceptual noise is large (as with the briefly presented stimuli in Experiment 1). A body of evidence converges in suggesting that a regulatory fit might increase cortical dopamine levels (Maddox et al., 2006). Briefly, the evidence includes work that has suggested a relationship between positive affect and cortical dopamine levels (Ashby, Isen, & Turken, 1999; Isen, 1993, 1999) and a relationship between global regulatory focus and frontal brain activation (Amodio, Shah, Sigelman, Brazy, & Harmon-Jones, 2004; Cunningham, Raye, & Johnson, 2005). Increased cortical dopamine is thought to increase the signal-to-noise ratio on projections from sensory representation areas with prefrontal cortical working memory cells (Ashby & Casale, 2003; Ashby et al., 2005). An increase in signal-to-noise ratio should increase sensitivity, leaving the response bias unaffected. Although based on solid neurobiological evidence, this proposal requires further study.

Previous work suggested that a regulatory fit might affect the placement of the decision criterion in identification. This did not occur in the high-perceptual-noise situation of Experiment 1, but did occur in the low-perceptual-noise situation of Experiment 2. As in the previous research, those in a regulatory fit shifted response toward the higher-payoff options, a reward-maximizing criterion shift that inherently involves a trade-off with accuracy (Crowe & Higgins, 1997; Markman et al., 2005).

This work also has important clinical implications. A cardinal attribute of depression is decreased approach-related behavior, which is similar in spirit to a decreased ability to maintain a promotion focus (Davidson, 1998; Sloan, Strauss, & Wisner, 2001; Watson et al., 1995). In one study, Pizzagalli et al. (2005) tested the hypothesis that depressed patients are insensitive to manipulations of the payoff structure because of reductions in their approach-related motivational system. The researchers used a two-stimulus identification task (which inspired our task) but, importantly, only gains were presented. Pizzagalli et al. showed that depressed patients had less-optimal decision criterion placement than controls. If depression induces a debilitated promotion focus, a prevention focus may be in effect, meaning that depressed patients with a gains reward structure are in a regulatory mismatch and might be expected to show suboptimal decision criterion placement. Some evidence in support of this hypothesis can be found in our own data. Furthermore, Experiment 2 suggests the intriguing hypothesis that depressed patients might perform better when required to minimize losses, as opposed to maximizing gains, because a losses reward structure would create a regulatory fit for patients with approach-related problems, leading to a de facto prevention focus.

The present research also adds to previous support that work in regulatory focus can inform the study of the conscious–unconscious distinction. Markman et al. (2007) made the case that either explicit or implicit processing may become preferentially activated due to the current regulatory state. The present experiments further this distinction by suggesting that task demands dictate which aspects of implicit perceptual processing are affected by regulatory focus (i.e., sensitivity or bias).

In conclusion, a fit between global regulatory focus and local reward structure affects perceptual tasks as well as cognitive tasks. When perceptual noise is greater, regulatory fit leads to greater sensitivity than regulatory mismatch. When perceptual noise is less, regulatory fit leads to a shift in response bias toward the optimal reward-maximizing decision criterion.

Limitations

Although we are unable to support strong null effects for response bias in Experiment 1 and empirical discriminability in Experiment 2, our key findings are for the interactions of global situational incentives and local task reward. In Experiment 1, this interaction affected discriminability, while in Experiment 2 it affected response bias. These are both novel findings that demonstrate that motivational influences can interact to moderate low-level stimulus identification in important ways.

In the signal identification paradigm, it is possible that differences in empirical discriminability arise from a difference in variances between the perceptual distributions (as opposed to a difference in the distances between the distribution means). ROC curves would need to be constructed over several criterion levels to rule this out. Thus, we cannot conclude with certainty that the regulatory fit effect observed in Experiment 1 is solely due to an effect on sensitivity. Even so, it is clear that a regulatory fit effect does emerge in stimulus identification, and to our knowledge this has not been demonstrated previously.

One potential limitation of the present study is the use of different stimuli between the two experiments. In Experiment 1, line length was relevant, and in Experiment 2, the brightness of a gray patch was used. Although it is possible that line length is more likely to lead to regulatory fit effects on sensitivity and brightness more likely to lead to regulatory fit effects on response bias, we find this highly unlikely. Over the past 20 years, we have run numerous identification and classification studies using line length, brightness, and other simple perceptual dimensions as stimulus dimensions, and we have found no fundamental differences in their effects on performance. In fact, Sagiv and Bentin (2001) found that although humans can recognize schematic faces as a type of face, schematic faces are processed more like nonface stimuli. In our view, the most reasonable interpretation of these data is that the level of internal noise inherent in the two designs (high in Experiment 1 and low in Experiment 2) is the operative factor, leading to fit effects on sensitivity in Experiment 1 and fit effects on response bias in Experiment 2.

Our study also lacked a control condition without imposed incentives. While this could be a topic for future research, by imposing local, situational manipulations, we hoped to alter any initial or default motivational states that the participant may have presented with. Another topic for future research is the nature of the payoff manipulation and starting conditions of the stimulus identification task.

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