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3 authors:

Ruby Nadler
The University of Western Ontario

Rahel Rabi
Baycrest

John Paul Minda
The University of Western Ontario

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Better Mood and Better Performance: Learning Rule-Described Categories Is Enhanced by Positive Mood

Ruby T. Nadler, Rahel Rabi, and John Paul Minda
The University of Western Ontario

Abstract

Theories of mood and its effect on cognitive processing suggest that positive mood may allow for increased cognitive flexibility. This increased flexibility is associated with the prefrontal cortex and the anterior cingulate cortex, both of which play crucial roles in hypothesis testing and rule selection. Thus, cognitive tasks that rely on behaviors such as hypothesis testing and rule selection may benefit from positive mood, whereas tasks that do not rely on such behaviors should not be affected by positive mood. We explored this idea within a category-learning framework. Positive, neutral, and negative moods were induced in our subjects, and they learned either a rule-described or a non-rule-described category set. Subjects in the positive-mood condition performed better than subjects in the neutral- or negative-mood conditions in classifying stimuli from rule-described categories. Positive mood also affected the strategy of subjects who classified stimuli from non-rule-described categories.

Keywords

frontal lobe, emotions, hypothesis testing, selective attention, response inhibition

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A well-established finding is that mood interacts with cognitive processing (for a review, see Isen, 1999), with executive functioning implicated as a possible source of the effects of this interaction (Mitchell & Phillips, 2007). Positive mood leads to enhanced cognitive flexibility,[1] whereas negative mood may reduce (or may not affect) cognitive flexibility (for a review, see Ashby, Isen, & Turken, 1999). Category learning has also been associated with cognitive flexibility (Ashby et al., 1999; Maddox, Baldwin, & Markman, 2006), making category learning well suited to the study of the effects of mood on cognition. For example, Ashby, Alfonso-Reese, Turken, and Waldron (1998) predicted that depressed subjects should be impaired in learning rule-described (RD) category sets. Smith, Tracy, and Murray (1993) supported this prediction and also found that depressed subjects were not impaired when learning non-RD categories. However, the more general question of how induced positive and negative mood states influence category learning remains unanswered. We addressed this question by using two kinds of categories, one in which learning is thought to be enhanced by cognitive flexibility and one in which learning is not thought to be enhanced by cognitive flexibility (Maddox et al., 2006).

Our starting point was the competition between verbal and implicit systems (COVIS) theory, which posits the existence of separate explicit and implicit category-learning systems (Ashby et al., 1998). The explicit system enables people to learn RD categories and is associated with the prefrontal cortex (PFC) and the anterior cingulate cortex (ACC). RD category learning uses hypothesis testing, rule selection, and inhibition to find and apply rules that can be verbalized, and it is influenced by cognitive flexibility. The implicit system enables people to learn non-RD categories, relies on connections between visual cortical areas and the basal ganglia, and is not affected by cognitive flexibility. This system is likely procedural in nature and dependent on a dopamine-mediated reward signal (Maddox, Ashby, Ing, & Pickering, 2004). RD and non-RD category sets have been dissociated behaviorally (for a review, see Maddox & Ashby, 2004) and neurobiologically (Nomura et al., 2007), making them appropriate for the study of mood effects.

We argue that positive mood increases cognitive flexibility, and this effect enhances the explicit category-learning system

Corresponding Author:
Ruby T. Nadler, The University of Western Ontario, Department of Psychology, Social Science Centre, Room 7418, 1151 Richmond St., London, Ontario, Canada N6A 5C2
E-mail: rnadler@uwo.ca

mediated by the PFC (Ashby et al., 1999; Ashby & Ell, 2001; Minda & Miles, 2010). We base our predictions on two lines of research. First, Ashby et al. (1999) hypothesized that positive affect is associated with enhanced cognitive flexibility as a result of increased dopamine in the frontal cortical areas of the brain. Second, the COVIS theory predicts that increased dopamine in the PFC and ACC should enhance learning on RD tasks, and reduced dopamine should impair learning on RD tasks (Ashby et al., 1998). Thus, positive mood should be associated with enhanced RD category learning, an important prediction that has not to our knowledge been tested directly.

We induced a positive, neutral, or negative mood in subjects and presented them with one of two kinds of category sets that have been widely used in the category-learning literature (Ashby & Maddox, 2005). These sets consisted of sine-wave gratings (Gabor patches) that varied in spatial frequency and orientation. The RD set of Gabor patches required learners to find a single-dimensional rule in order to correctly classify the stimuli on the basis of frequency but not orientation, and the non-RD, information-integration (II) set of Gabor patches required learners to assess both orientation and frequency. Subjects in the RD condition were able to formulate a verbal rule to ensure optimal performance, but subjects in the II condition were not able to form a rule that could be easily verbalized.

We predicted that subjects in a positive mood, compared with those in a neutral or negative mood, would perform better when learning RD categories. It was unclear whether a negative mood would impair RD learning relative to a neutral mood, as the effects of negative mood on cognitive processing are variable and difficult to predict (for a review, see Isen, 1990). Because the PFC and the ACC do not mediate the implicit system, we did not expect mood to affect II category learning.

Method

Subjects

Subjects were 87 university students (61 females and 26 males), who received $10.00 or course credit for participation. Subjects were randomly assigned to one of the three mood-induction conditions and one of the two category sets. Six subjects who scored below 50% on the categorization task were excluded from data analysis.

Materials

We used a series of music clips and video clips from YouTube[2] to establish affective states. We verified that these clips evoked the intended emotions by conducting a pilot study. After each viewing or listening, subjects in the pilot study (7 graduate students, who did not participate in the main experiment) rated how the clip made them feel on a 7-point scale, which ranged from 1 (*very sad*) to 4 (*neutral*) to 7 (*very happy*). Table 1 shows the complete list of clip selections and the average ratings by pilot subjects; it also denotes the clips selected for the main experiment. As a manipulation check during the main experiment, we queried subjects with the Positive and Negative Affect Schedule (PANAS) after using the selected clips to induce moods. The PANAS assesses positive and negative affective dimensions (Watson, Clark, & Tellegen, 1988).

Table 1. Music and Video Clips Used in the Pilot Study

Selection	Average subject rating
Positive music	
Mozart: "Eine Kleine Nachtmusik—Allegro"*	6.57
Handel: "The Arrival of the Queen of Sheba"	5.00
Vivaldi: "Spring"	6.14
Neutral music	
Mark Salona: "One Angel's Hands"*	3.86
Linkin Park: "In the End (Instrumental)"	4.14
Stephen Rhodes: "Voice of Compassion"	3.29
Negative music	
Schindler's List Soundtrack: "Main Theme"*	2.00
I Am Legend Movie Theme Song	2.71
Distant Everyday Memories	2.57
Positive video	
Laughing Baby*	6.57
Whose Line Is It Anyway: Sound Effects	6.43
Where the Hell Is Matt?	6.00
Neutral video	
Antiques Roadshow Television Show*	4.14
Facebook on *60 Minutes*	3.71
Report About the Importance of Sleep	4.29
Negative video	
Chinese Earthquake News Report*	1.43
Madison's Story (About Child With Cancer)	1.71
Death Scene From the Film *The Champ*	1.86

Note: Clips were taken from the YouTube Web site. Asterisks denote clips that were used in the main experiment.

The Gabor patches used in the main experiment were generated according to established methodologies (see Ashby & Gott, 1988; Zeithamova & Maddox, 2006). For each category (RD and II), we randomly sampled 40 values from a multivariate normal distribution described by that category's parameters (shown in Table 2). The resulting structures for the RD and II category sets are illustrated in Figure 1.[3] We used the PsychoPy software package (Pierce, 2007) to generate a Gabor patch corresponding to each coordinate sampled from the multivariate distributions.

Procedure

In the main experiment, subjects were assigned randomly to one of three mood-induction conditions (positive, neutral, or negative), as well as to one of two category sets (RD or II).

Table 2. Distribution Parameters for the Rule-Described and Non-Rule-Described Category Sets

Category set and category	μ_f	μ_o	σ_f^2	σ_o^2	$cov_{f,o}$
Rule-described					
Category A	280	125	75	9,000	0
Category B	320	125	75	9,000	0
Non-rule-described					
Category A	268	157	4,538	4,538	435
Category B	332	93	4,538	4,538	4,351

Note: Dimensions are in arbitrary units; see Figure 1 for scaling factors. The subscripted letters *o* and *f* refer to orientation and frequency, respectively.

Subjects were presented with the clips (music first, then video) from their assigned mood condition and then completed the PANAS so we could ensure that the mood induction was successful.

After receiving instructions, subjects performed a category-learning task on a computer. On each trial, a Gabor patch appeared in the center of the screen, and subjects pressed the "A" or the "B" key to classify the stimulus. Subjects who viewed the RD category set (Fig. 1a) had to find a single-dimensional rule to correctly classify the stimuli on the basis of the frequency of the grating, while ignoring the more salient dimension of orientation. The optimal verbal rule for such classification could be phrased as follows: "Press 'A' if the stimulus has three or more stripes; otherwise, press 'B.'" The non-RD, II category set (Fig. 1b) required learners to assess both orientation and frequency. There was no rule for this set that could be easily verbalized to allow for optimal performance. In both conditions, feedback ("CORRECT" or "INCORRECT") was presented after each response. Subjects completed four unbroken blocks of 80 trials each (320 total). The presentation order of the 80 stimuli was randomly generated within each block for each subject.

Results

PANAS

Scores on the Positive Affect scale were as follows—positive-mood condition: 2.89; neutral-mood condition: 2.45; and negative-mood condition: 2.42. A significant effect of mood on positive affect was found, $F(2, 78) = 3.98$, $p < .05$, $\eta^2 = .093$. Positive-mood subjects showed only marginally more positive

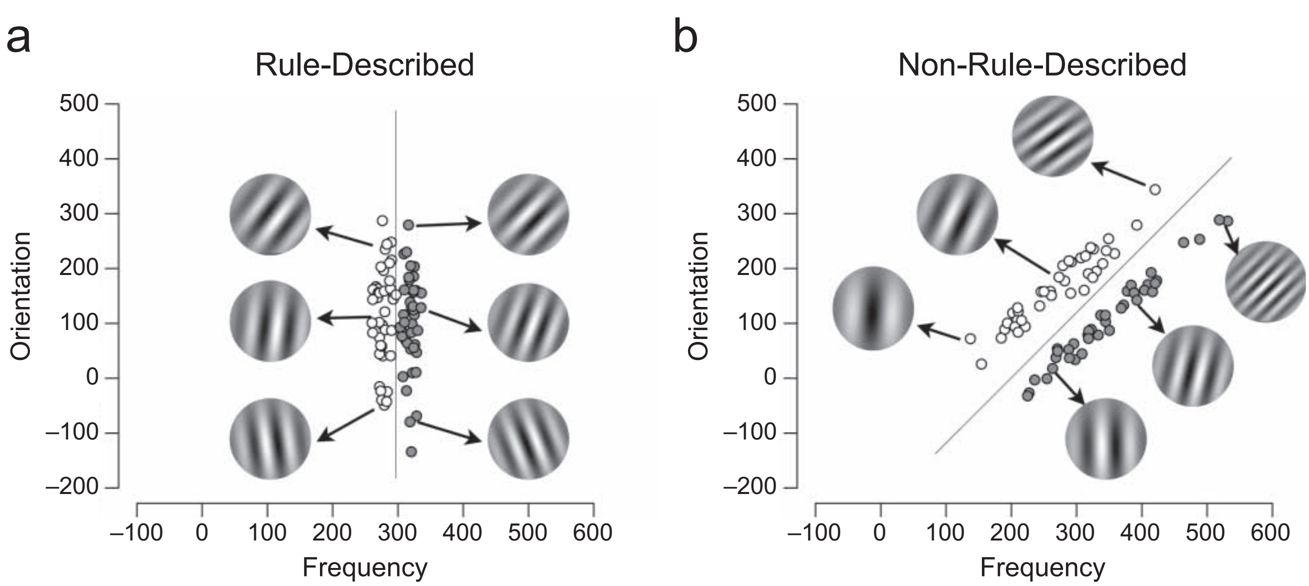

Fig. 1. Structures used in the (a) rule-described category set and (b) non-rule-described, information-integration category set. Category A stimuli are represented by light circles, and Category B stimuli are represented by dark circles. The solid lines show the optimal decision boundaries between the stimuli. The values of the stimulus dimensions are arbitrary units. Each stimulus was created by converting the value of these arbitrary units into a frequency value (cycles per stimulus) and an orientation value (degree of tilt). For both category sets, the grating frequency (*f*) was calculated as 0.25 + (x_f/50) cycles per stimulus, and the grating orientation (*o*) was calculated as *xo* × (π/20)°. The Gabor patches are examples of the actual stimuli seen by subjects.

affect than neutral-mood subjects did ($p < .06$), but they showed significantly more positive affect than negative-mood subjects did ($p < .05$). These scores indicate that the mood-induction procedures were effective. Scores on the Negative Affect scale were as follows—positive-mood condition: 1.15; neutral-mood condition: 1.18; and negative-mood condition: 2.13. A significant effect of mood on negative affect was found, $F(2, 78) = 30.36$, $p < .001$, $\eta^2 = .438$, with negative-mood subjects showing significantly more negative affect than positive- and neutral-mood subjects did ($p < .0001$ in both cases). These results again indicate that the mood-induction procedures were effective.

Category learning

Figure 2 shows the learning curve (average proportion of correct responses in Blocks 1–4) for each condition and each category set. A mixed analysis of variance revealed main effects of category set, $F(1, 75) = 31.94$, $p < .001$, $\eta^2 = .257$; mood, $F(2, 75) = 4.40$, $p < .05$, $\eta^2 = .071$; and block, $F(3, 225) = 41.33$, $p < .001$, $\eta^2 = .322$. It also revealed a significant interaction between mood and category set, $F(2, 75) = 4.17$, $p < .05$, $\eta^2 = .067$. We conducted two separate analyses of variance (one for the RD category and one for the II category) to examine this interaction.

A main effect of mood on overall performance was found for the RD category set, $F(2, 35) = 6.28$, $p < .001$, $\eta^2 = .264$. A Tukey's honestly significant difference test showed that overall performance by subjects in the positive-mood condition ($M = .85$) was higher than performance by subjects in the negative-mood condition ($M = .73$, $p < .0001$) and subjects in the neutral-mood condition ($M = .73$, $p < .0001$). Performance did not differ between subjects in the neutral- and negative-mood conditions ($p = .69$). No effect of mood on overall performance was found for the II category set ($p = .71$). Overall proportions correct were as follows—positive-mood condition: .64; negative-mood condition: .66; and neutral-mood condition: .64.

Computational modeling

For insight into the response strategies used by our subjects, we fit decision-bound models to the first block of each subject's data (for details, see Ashby, 1992a; Maddox & Ashby, 1993). We analyzed the first block of trials because that is when mood-induction effects are likely to be strongest, and it is also when cognitive flexibility is most needed. One class of models assumed that each subject's performance was based on a single-dimensional rule (we used an optimal version with a fixed intercept and a version with the intercept as a free parameter). Another class of models assumed that each subject's performance was based on the two-dimensional II boundary (we used an optimal version with a fixed intercept and slope, a version with a fixed slope, and a version with a freely varying

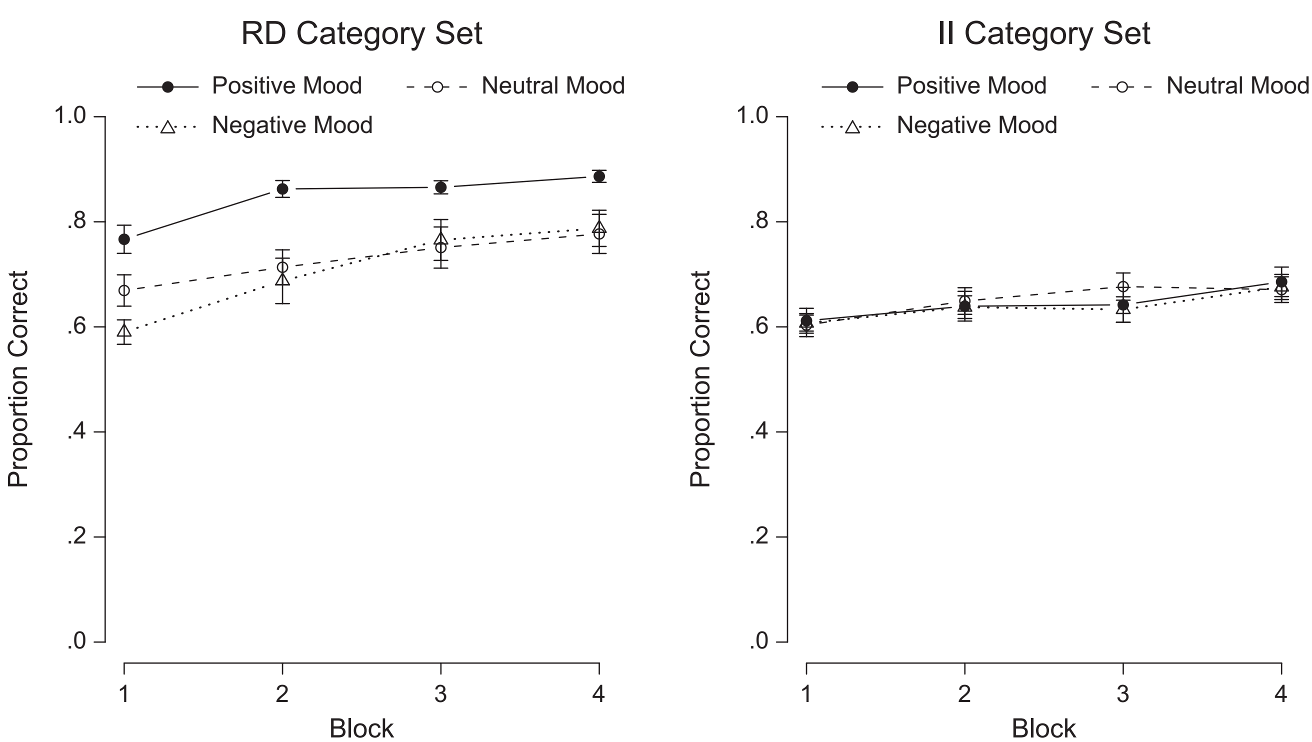

Fig. 2. Average proportion of correct responses to stimuli in the three mood conditions as a function of trial block. Subjects were tested on either the rule-described (RD) category set (left graph) or the non-RD, information-integration (II) category set (right graph). Error bars denote standard errors of the mean.

slope and intercept). We fit these models to each subject's data by maximizing the log likelihood. Model comparisons were carried out using Akaike's information criterion, which penalizes a model for the number of free parameters (Ashby, 1992b). The proportion of subjects whose responses were best fit by their respective optimal model is shown in Figure 3. For the RD categories, .83 of positive-mood subjects, .62 of neutral-mood subjects, and .54 of negative-mood subjects were fit best by a model that assumed a single-dimensional rule. For the II categories, .71 of positive-mood subjects, .40 of neutral-mood subjects, and .43 of negative-mood subjects were fit best by one of the II models.

Discussion

In this experiment, positive, neutral, and negative moods were induced before subjects learned either an RD or a non-RD, II category set. The RD set required subjects to use hypothesis testing, rule selection, and response inhibition to achieve optimal performance, and the II set was best learned by associating regions of perceptual space with responses (Ashby & Gott, 1988). We found that positive mood enhanced RD learning compared with neutral and negative moods. Mood did not seem to affect II learning. However, a comparison of decision-bound models suggested that positive-mood subjects displayed a greater degree of cognitive flexibility compared with neutral- and negative-mood subjects by adopting an optimal strategy early in both RD and II learning.

The COVIS theory suggests that people learn categories using an explicit, rule-based system or an implicit, similarity-based system (Ashby et al., 1998; Ashby & Maddox, 2005; Minda & Miles, 2010). The brain areas that mediate these systems have been well studied, linking the PFC, ACC, and medial temporal lobes to the explicit system but not to the implicit system. Our experiment highlights a variable that facilitates the learning of RD categories using the explicit system.

The finding that positive mood enhances performance of the explicit system posited by the COVIS theory corresponds with the dopamine hypothesis of positive affect (Ashby et al., 1999). Our results connect this research with existing work on category learning, and we view this connection as a substantial step forward in the study of cognition and mood. We suspect that our positive-mood subjects experienced increased cognitive flexibility, which allowed them to find the optimal verbal rule faster than negative-mood subjects and neutral-mood subjects did. Performance on the II category set did not differ strongly across the different mood conditions. This result is also in line with the dopamine hypothesis, as positive mood is not theorized to affect the same brain regions

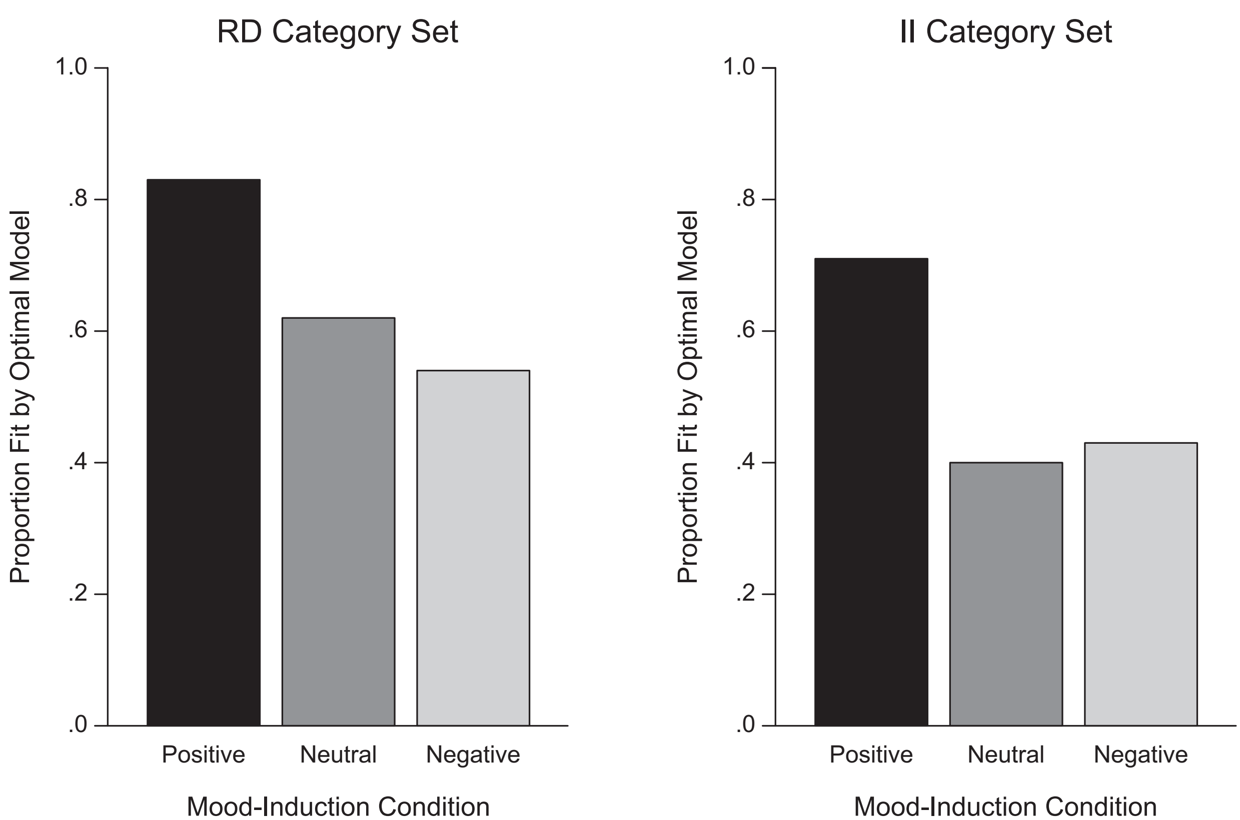

Fig. 3. Proportion of subjects in each mood-induction condition whose responses best fit the optimal model for the category set to which they were assigned. Subjects learned either the rule-described (RD) category set (left graph) or the non-RD, information-integration (II) category set (right graph).

hypothesized by the COVIS theory to be involved with the learning of non-RD category sets. However, our modeling results suggest that the cognitive flexibility associated with positive mood may affect the strategies used in II category learning. This cognitive flexibility could allow the explicit system to exhaust rule searches more effectively, even though performance levels may remain unchanged between the conditions.

We failed to find an effect of negative mood in RD learning. This is in line with previous research that reported no differences between negative- and neutral-mood subjects on measures of cognitive flexibility (Isen, Daubman, & Nowicki, 1987). It may be that negative mood does not affect RD category learning, although we think it could, given the right circumstances. One possible explanation of why we did not find such an effect is that the induced negative mood may not have been sustained long enough to interfere with performance. We suspect that subjects in certain negative states will be impaired in RD category learning. Future work should examine ways of sustaining mood states and should explore a wider range of negative mood states.

An intriguing possibility that was not observed is that negative mood could enhance II category learning. Recent research suggests that affective states low in motivational intensity (e.g., amusement, sadness) are associated with broadened attention, and affective states high in motivational intensity (e.g., desire, disgust) are associated with narrowed attention (Gable & Harmon-Jones, 2008, 2010). Thus, for example, sadness may facilitate performance when broadened attention is beneficial for category learning. We did not find this effect, either because learning of the II category set used did not benefit from broadened attention or because the induced negative mood was high in motivational intensity. These interesting ideas require further research.

Smith et al. (1993) showed that clinically depressed subjects were impaired in RD category learning and unimpaired in II category learning, but our research is the first to investigate how experimentally induced mood states influence category learning. We have shown that positive mood enhanced the learning of an RD category set, an advantage that was strong and sustained throughout the task. Positive mood did not improve the learning of II categories, though there was evidence that positive mood enhanced selection of the optimal strategy. By connecting theories of multiple-system category learning and positive affect, our research suggests that positive affect enhances performance when category learning benefits from cognitive flexibility. Future work should examine the interaction between mood states (motivationally weak compared with intense), valence (positive compared with negative), and category type (explicit compared with implicit) in category learning.

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Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Notes

1. We define cognitive flexibility as the ability to seek out and apply alternate strategies to problems (Maddox, Baldwin, & Markman, 2006) and to find unusual relationships between items (Isen, Johnson, Mertz, & Robinson, 1985).
2. The clips can be found by searching for their titles on YouTube (http://www.youtube.com/), or URLs can be obtained from the first author.
3. Stimulus parameters and generation were the same as those used by Zeithamova and Maddox (2006).

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