The Absence of Positive Affect is Associated with Complex Rule Use

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Abstract

Two experiments explore the effects of mood on category learning. In the first experiment subjects were put into either a negative or a neutral mood before completing one of two category-learning tasks. Negative mood briefly impaired rule-based category learning but this impairment did not persist throughout the task. Negative mood did not influence non-rule-based learning. In a second study subjects learned one of three category sets (easy rule-based, hard rule-based, non-rule-based) by Shepard, Hovland & Jenkins (1961) and completed the Beck Depression Inventory (BDI-II). A significant negative correlation was found between hard rule-based performance and subject scores on the BDI-II. No significant correlations were found between subject scores on the BDI-II and easy rule-based or non-rule-based performance. These results suggest that negative affect does not significantly impair category learning but the absence of positive affect (as measured by the BDI-II) is negatively related to complex rule use.

Keywords: Negative affect; category learning; multiple systems; rule use.

Introduction

The COmpetition between Verbal and Implicit Systems (COVIS) theory of category learning posits the existence of at least two separate but competing systems (Ashby, Alfonso-Reese, Turken & Waldron, 1998). The first is the explicit system, which is used to solve verbalizable/rule-based category sets. The second is the implicit system, which is used to solve category sets for which there is no easily verbalizable rule (such as family resemblance categories). Learning in the second system takes longer and involves the association of a category response (A or B) with a stimulus via a dopamine mediated reward signal involving the tail of the caudate nucleus. In contrast, the explicit system can learn quickly and involves the formulation, selection and execution of rules. The prefrontal cortex (PFC) and anterior cingulate cortex (ACC) are theorized to be involved with this system, and dopamine is also important in this system.

The COVIS theory hypothesizes that subjects experiencing a reduction of dopamine in the ACC should be impaired on explicit rule-based tasks. Conversely, subjects experiencing an increase of dopamine should experience enhanced learning in explicit rule-based tasks. Ashby, Isen, and Turken (1999) hypothesized that positive affect is associated with increased dopamine levels in the brain, specifically in the same areas implicated by COVIS in the explicit category learning system. Therefore positive affect should be associated with enhanced rule-based category learning. This prediction was tested recently by Nadler, Rabi, and Minda (2010), who found that subjects in a positive mood displayed better overall rule-based category learning performance compared to a neutral mood group.

Predictions about negative affect are less straightforward, as noted by Ashby et al. (1999). Negative affect has not been proven to be the simple converse of positive affect. Isen, Daubman, and Nowicki (1987) reported that positive affect subjects performed better than neutral affect subjects on a problem-solving task. However negative affect subjects did not differ from neutral affect subjects. In a review of the evidence, Isen (1987) describes the effects of positive and negative affect as independent and nonsymmetrical as opposed to inverse or similar. Despite these findings, the idea that negative affect should impair cognition at least some of the time persists.

Nadler et al. (2010) also compared a negative affect group with a neutral affect group, and reported that negative mood did not impair overall performance on rule-based or non-rule-based category learning. However by focusing on overall performance across 320 trials, it is possible that more subtle effects of negative mood were missed. Experiment 1 presents a reanalysis of the Nadler et al. (2010) negative mood data to explore the influence of negative affect on category learning in greater depth.

Study 1

Method

Subjects 56 undergraduates from the University of Western Ontario participated for pay, 28 in the negative mood condition and 28 in the neutral mood condition.

Materials *Youtube clips.* Music and video clips taken from the video website YouTube (http://www.youtube.com) were used to manipulate mood states. For the negative mood condition subjects listened to the soundtrack from the movie "Schindler's List", and then watched footage of the 2008 Chinese Earthquake. Subjects in the neutral mood condition listened to a piece of music called "One Angel's Hands" by Mark Salona and then watched footage from the televisionshow “Antiques Roadshow”. Clip selections were based on a pilot study where 7 graduate students rated a series of clips in terms of how the clips made them feel using a 7-point scale, which ranged from 1 (*very sad*) to 4 (*neutral*) to 7 (*very happy*). The clips rated as most sad and most neutral were used in the current experiment.

Mood scale. The Positive And Negative Affect Schedule (PANAS) assesses positive and negative affect dimensions (Watson, Clark, & Tellegen, 1987), and was used to assess subjects’ mood after exposure to the music and video clips.

Category sets. Gabor patches were created using established methodologies (see Ashby & Gott, 1988; Zeithamova & Maddox, 2006). For each category set (rule-based and non-rule-based), 40 values from a multivariate normal distribution were randomly sampled. The resulting structures for the category sets are illustrated in Figure 1. The PsychoPy software package (Pierce, 2007) was used to generate Gabor patches corresponding to each coordinate sampled from the multivariate distributions.

Procedure Subjects were randomly assigned to one of two mood-induction conditions (neutral or negative), as well as to one of the two category sets (rule-based or non-rule-based). Subjects were presented with the YouTube clips from their respective condition, listening to the music clips first and then the video clips. Following exposure to the clips subjects completed the PANAS to assess their affective state.

After receiving instructions subjects completed the category-learning task on the computer. On each trial a Gabor patch (made to look like a crystal ball) was presented in the centre of the screen, and subjects pressed the “A” or the “B” key to classify the stimulus. Feedback “CORRECT” or “INCORRECT” was given after each trial. Subjects completed four blocks of 80 trials for a total of 320 trials. The presentation order of the stimuli was randomly generated within each block for each subject.

Upon completion of the 320 trials, subjects were asked if they had any questions and debriefed. Subjects in the negative mood condition were exposed to a happy video clip before leaving the experiment so that they were not in a negative mood upon leaving the experiment.

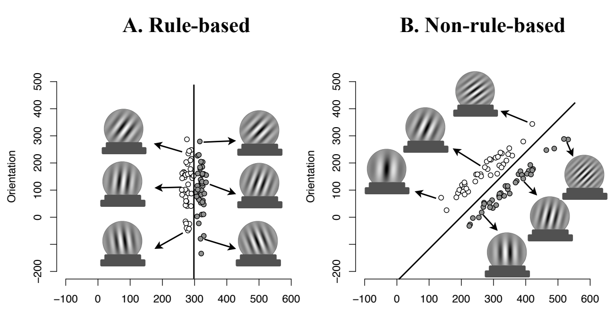

Figure 1: Category sets from Study 1: A. Rule-based category set. B. Non-rule-based category set.

Results

PANAS The averaged scores on the Negative Affect scale of the PANAS were 1.18 for the neutral condition and 2.13 for the negative condition, and this difference was significant, F (1,55) = 31.75, p < .001, n^2 = .366, with negative mood subjects reporting significantly more negative affect than neutral affect subjects.

Category learning When performance across all 320 trials of the rule-based learning task was compared, no significant differences were found between neutral (M=.73) and negative (M=.73) mood conditions, F (1, 27) = 0.18, p = .67. The 320 category learning trials were divided into 20 trial increments to see if subtle negative mood impairments could be found, but out of 16 20-trial blocks (shown above in Figure 2), there was only 1 block where there appeared to be a significant difference between neutral and negative conditions (Block 4).

Non-rule-based performance did not differ between neutral (M = .66) and negative (M = .64) mood conditions, F (1, 27) = 0.63, p = .43.

Computational Modeling The response strategies of our subjects were investigated using decision-bound models (for more information see Ashby, 1992a; Maddox & Ashby, 1993). One class of model assumed that the performance of each subject was based on a single-dimensional rule (the optimal version of this class used a fixed intercept, while the other allowed the intercept to vary). A second class assumed that the performance of each subject was based on a two-dimensional non-rule-described boundary (an optimal version with a fixed slope and intercept, a version with a fixed slope, and a version with a slope and intercept that were free to vary). The models were fit to each subject’s performance data by maximizing the log likelihood. Models were compared by using Akaike’s information criterion (Ashby, 1992b).

When the optimal rule-based model fit was compared across all 320 trials of rule-based category learning, there was no difference between the neutral (M = .75) and negative (M = .75) conditions. The optimal model fits by 80-trial block are shown below in Figure 3.

Discussion

The current experiment sought to explore the effects of negative mood on category learning. While overall performance between negative and neutral mood conditions did not differ, negative affect subjects briefly performed more poorly than neutral affect subjects. However this worsened performance was transient and did not persist throughout learning. Computational modeling did not reveal any major differences between the conditions. Overall negative affect subjects could not be distinguished from neutral affect subjects.

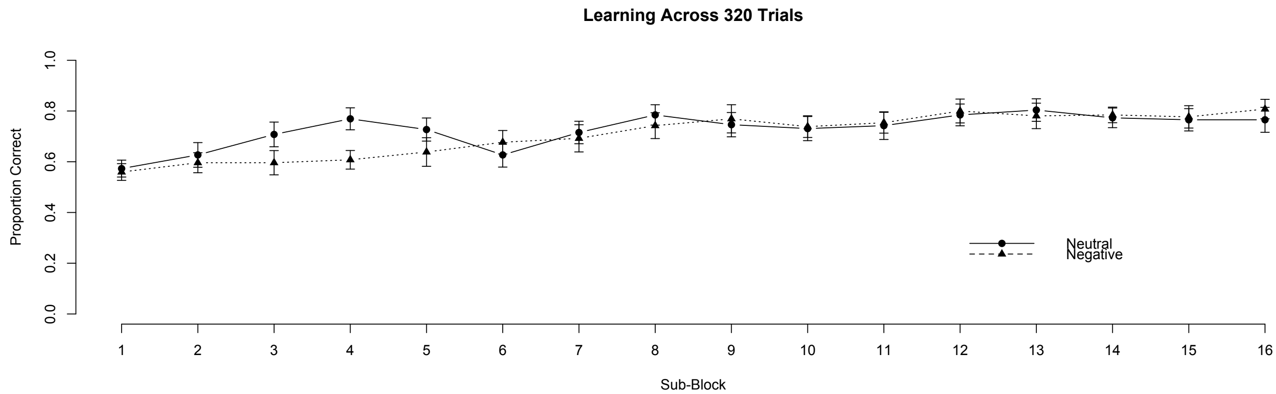

Figure 2: Category learning across all 320 rule-based category learning trials, divided by 20 trial increments

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It is possible that the negative mood the negative condition subjects experienced at the beginning of the category-learning task dissipated early on, resulting in equivalent performance with neutral mood subjects. Completing 320 trials of the category learning task typically takes around 30-40 minutes.This is in contrast with the sustained and strong positive affect advantage reported by Nadler et al. (2010). Isen (1990) provides one possible explanation for why negative mood effects do not mirror positive mood effects, and that is that subjects in a negative affective state actively resist staying in such a state. Ways of extending negative affect may be successful in producing stronger negative affect impairments. For example it is possible that if we had exposed subjects to negatively-valenced clips at regular intervals throughout learning that performance would have been more consistently impaired.

Non-rule-based category learning was not influenced by negative affect. This is in line with the COVIS model of category learning that distinguishes between verbal and implicit learning systems.

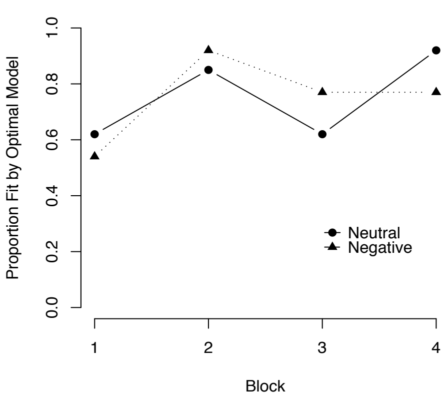


Figure 3: Proportion of rule-based category learning subjects best fit by the optimal model.

Experiment 2

Experiment 1's results suggest that negative affect does not strongly impair rule-based category learning, and does not seem to affect non-rule-based category learning at all.

However as noted in the introduction, negative affect is not the simple converse of positive affect, and perhaps should not be expected to produce the converse pattern that positive affect does. The COVIS model of category learning suggests that reduced dopamine should impair rule-based category learning. Reduced dopamine levels have been associated not with increased negative affect, but rather with a loss of positive affect, as evidenced by patients prescribed dopamine antagonists (Hyman & Nestler, 1993). It has been proposed that the mesolimbic dopamine reward circuit, which overlaps to some extent with the COVIS model's explicit system, is involved with clinical depression (Nestler & Carlezon, 2006). Thus depression may represent a real life example of a condition that results in reduced dopamine in frontal brain regions, and consequently an opportunity to evaluate the COVIS theory of category learning.

Only one study has previously explored this idea. Smith, Tracy, and Murray (1993) compared a group of adults who were classified as severely depressed with age-matched controls on two kinds of category sets. The first category set required subjects to find a verbalizable rule to achieve perfect performance. The second category set could be learned using overall similarity/family resemblance, and thus did not require verbal rule use. Depressed subjects were found to be impaired on rule-based but not non-rule-based category learning.

Experiment 2 is a correlational study that correlated a depression scale with performance on one of three category sets, two of which are rule-based and one of which is non-rule-based. We expected to find a relationship between reported depression symptoms and rule-based category learning, in line with past research by Smith et al. (1993), as well as the COVIS model.

Method

Subjects 80 university undergraduates from the University of Western Ontario participated either for pay or for course credit, with 23 subjects in the easy rule-based condition (ERB), 27 subjects in the hard rule-based condition (HRB), and 30 subjects in the non-rule-based condition (NRB).

Materials The Beck Depression Inventory (BDI-II; Beck, Steer, & Brown, 1996) is made up of 21 groups of statements that assess the features of major depression (e.g. sadness, loss of pleasure, changes in sleep, etc.). Subjects are asked to think about how they have felt for the last two weeks when responding.

Category sets. Three category sets designed by Shepard, Hovland, and Jenkins (1961) were used. In each category set there are 3 features (shape, size, colour) that can have one of two dimensions (square or triangle, large or small, orange or blue). In the first category set (easy rule-based/Type I), only one feature is used to indicate category membership, subjects can achieve perfect performance using a single-dimensional verbal rule. In the second category set used (hard rule-based/Type II), more than one feature is used to indicate category membership, subjects can achieve perfect performance using a disjunctive verbal rule (i.e. dark triangles and light squares in one category, light triangles and dark squares in another category). In the third category set used (non-rule-based/Type IV), more than one feature is used to indicate category membership and subjects can achieve perfect performance by learning that the stimuli in each category share family resemblance. These category sets are shown in Figure 4.

Procedure Upon agreeing to participate, subjects completed the depression questionnaire using paper and pencil. Subjects were then randomly assigned to one of the three category learning conditions (easy rule-based, hard rule-based, and non-rule-based) and completed 80 trials of the task on a computer. Subjects saw each stimulus on a computer screen and were instructed to press the "0" or the "1" key to indicate that the shape belonged in the forest or the mountains respectively. After responding, subjects were given feedback: the shape would smile and move towards the correct location on the screen to indicate a correct response, or the shape would frown and move half-way towards the incorrect location and then smile and move to the correct location to indicate an incorrect response. Another trial began once feedback was received. Stimuli were presented in a random order within each block of 8 stimuli and blocks were presented in an unbroken fashion.

Results

BDI-II Scores The BDI-II groups subjects into 4 groups: minimal depression (0-13), mild depression (14-19), moderate depression (20-28), and severe depression (29-63). The majority (N=59) of our subjects scored within the minimal depression range, 11 scored within the mild depression range, 6 in the moderate range, and 3 subjects scored in the severe depression range. As this was a between-subjects experiment, the depression scores of subjects is divided by category set completed in Table 1.

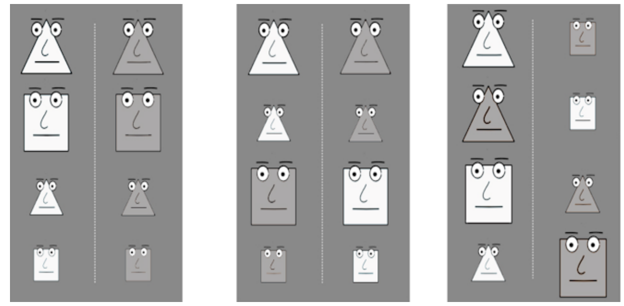


Figure 4: Shepard, Hovland, & Jenkins (1961) category sets (from left to right): easy rule-based (Type I), hard rule-based (Type II), and non-rule-based (Type IV).

Table 1: Subject depression symptoms. Depression classifications taken from the BDI-II. Minimal = 0-13, mild = 14-19, moderate = 20-28, severe = 29-63. ERB = Easy-rule-based, HRB = Hard-rule-based, NRB = Non-rule-based.

Depression	ERB	HRB	NRB
Minimal	18	22	19
Mild	1	2	8
Moderate	1	3	2
Severe	2	0	1

Category Learning Performance Subjects performed 10 blocks (80 trials) of one of the three category sets. The averaged performance of subjects who learned the easy rule-based category set was M = 85.63, sd = 16.70. The averaged performance of subjects who learned hard rule-based category set was M = 68.08, sd = 15.59. The averaged performance of subjects who learned the non-rule-based category set was M = 67.92, sd = 13.56. The learning curve of all three category types across 80 trials (10 blocks) of learning is shown in Figure 5.

Correlational Analyses Pearson, 2-tailed correlational analyses were performed between subjects averaged performance across all ten blocks of category learning performance and the BDI-II. There were no significant correlations between subject scores on the BDI-II and easy rule-based or non-rule-based category learning ($p > .05$ for both). There was a significant negative correlation between hard-rule-based performance and BDI-II score $r = -.541$, $p < .01$. A scatter plot showing subject's overall performance and BDI-II responding on Type II category learning is shown in Figure 6.

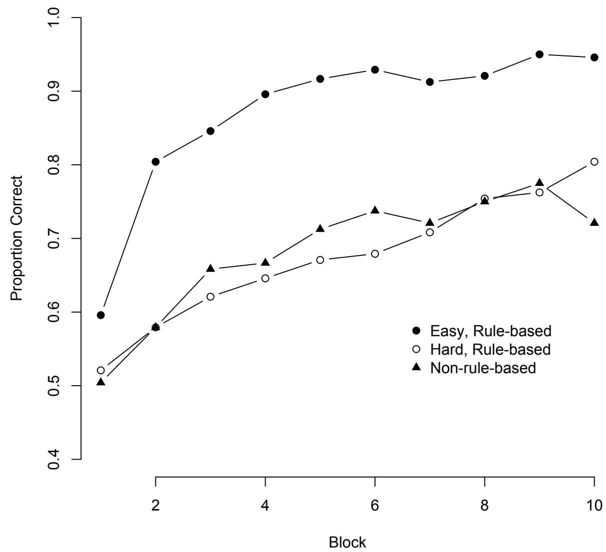
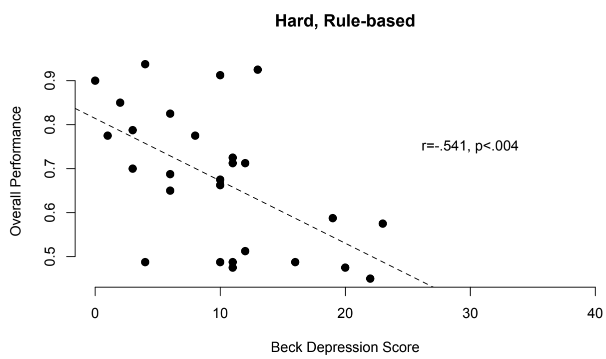


Figure 5: Proportion correct across ten blocks for the Easy, Rule-based, Hard, Rule-based, and Non-rule-based category sets.



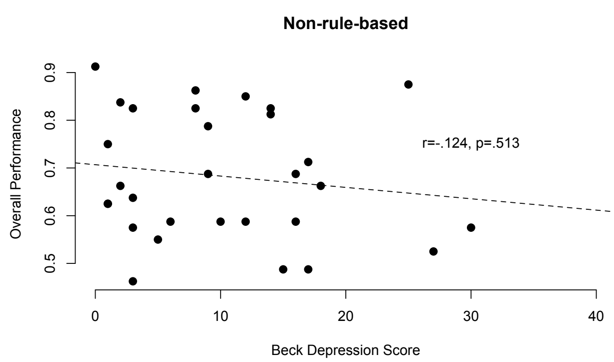


Figure 6: Scatter plot of BDI-II scores and overall performance on the hard, rule-based, and the non-rule-based category sets.

Discussion

The current experiment explored the relationship between rule-based and non-rule-based category learning and a measure of depression symptoms. Although both easy rule-based/Type I and hard rule-based/Type II category sets are learned by with a verbal rule using the explicit system, the hard rule-based category set involves the learning of a complicated, disjunctive rule while easy rule-based set involves the learning of a simple, one-dimensional rule. In contrast, the non-rule-based category set can be learned nonverbally, by the implicit system. We predicted that subjects who scored higher on the BDI-II would be: unimpaired on easy rule-based learning, impaired on hard rule-based learning, and unimpaired on non-rule-based learning. This is because depressive symptoms should be related to the verbal category learning system but not to the extent that subjects cannot learn a simple verbal rule, however a more complex verbal rule should prove problematic for subjects who scored higher on the BDI-II. Since the brain areas implicated in the nonverbal system are theorized to not be influenced by changes in dopamine in frontal brain regions, we predicted that there would be no correlation between performance on this task and BDI-II score.

As predicted, there was a negative relationship between BDI-II score and hard rule-based category learning performance, but no relationship between BDI-II score and easy rule-based, or non-rule-based performance. Previous work by Smith et al. (1993) showed that subjects experiencing major depression were impaired on criterial attribute (rule-based) category learning but unimpaired on family resemblance (non-rule-based) category learning. While the present findings seem to fit with this research, it must be noted that we did not have as many subjects in our experiment who could be categorized as having major depression, preventing clear comparisons from being made.

A limitation of this work is that the study is correlational, so no causal conclusions can be drawn. A further limitation is that the majority of our subjects were not clinically depressed. However this work indicates that individual differences in the degree of depressive symptoms are related to complex rule-based category learning performance.

Conclusions

Experiment 1 did not find that negative affect consistently impairs category-learning performance; indeed only a single instance of significant impairment was found when learning was examined in detail. These results warrant replication and further investigation. Future work should utilize different methods of inducing negative affect as well as methods of sustaining negative affect throughout the experiment.

Experiment 2 offers some interesting links between depression symptoms and category learning performance. Although the conclusions that can be drawn from this study are limited, it appears that depressive symptoms are related to complex rule-based category learning even when subjects do not meet the criteria for major/clinical depression. These findings are in line with the work of Smith et al. (1993) and represent a first attempt to revivify the study of depression and category learning. Future research should extend this work by comparing the category learning performance of depressed and non-depressed subjects on a wider variety of category sets.

The research presented suggests that depressive symptoms may be related to performance on rule-based category learning tasks that are moderately difficult, while negative affect may not impair either rule-based or non-rule-based category learning. Both experiments require replication and extensions, but we think this work is a step towards systematically demonstrating that depressive symptoms, not negative affect, influence the explicit category learning system.

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References

Ashby, F.G. (1992a). Multidimensional models of categorization. In F.G. Ashby (Ed.), Multidimensional models of perception and cognition (pp. 449–483). Hillsdale, NJ: Erlbaum.

Ashby, F.G. (1992b). Multivariate probability distributions. In F.G. Ashby (Ed.), Multidimensional models of perception and cognition (pp. 1–34). Hillsdale, NJ: Erlbaum.

Ashby, F. G., Alfonso-Reese, L. A., Turken, A. U., & Waldron, E. M. (1998). A neuropsychological theory of multiple systems in category learning. *Psychological review, 105,* 442-481.

Ashby, F.G., Isen, A.M., & Turken, A.U. (1999). A neuropsychological theory of positive affect and its influence on cognition. *Psychological review, 106,* 529-550.

Beck, A.T., Steer, R.A., & Brown, G.K. (1996) Beck Depression Inventory-II. San Antonio, TX: The Psychological Corporation.

Hyman, S. E., & Nestler, E. J. (1993). The molecular foundations of psychiatry. Washington, DC: American Psychiatric Press.

Isen, A.M. (1990). The influence of positive and negative affect on cognitive organization: Some implications for development. In N.L. Stein, B. Leventhal, & T.R. Trabasso (Eds.), *Psychological and biological approaches to emotion* (pp. 75–94). Hillsdale, NJ: Erlbaum.

Isen, A.M., Daubman, K.A., & Nowicki, G.P. (1987). Positive affect facilitates creative problem solving. *Journal of Personality and Social Psychology, 52*, 1122–1131.

Maddox, W.T., & Ashby, F.G. (1993). Comparing decision bound and exemplar models of categorization. Perception & Psychophysics, 53, 49–70.

Nadler, R. T., Rabi, R., & Minda, J. P. (2010). Better mood and better performance: learning rule-described categories is enhanced by positive mood. *Psychological Science*, 21, 1770-1776.

Nestler, E. J., & Carlezon, W. A. (2006). The mesolimbic dopamine reward circuit in depression. *Biological Psychiatry, 59*, 1151-1159.

Pierce, J. (2007). PsychoPy—Psychophysics software in Python. *Journal of Neuroscience Methods, 162*, 8–13.

Shepard, R.N., Hovland, C.L., & Jenkins, H.M. (1961). Learning and memorization of classifications. *Psychological Monographs, 75*(13, Whole No. 517).

Smith J.D., Tracy, J.I., & Murray, M.J. (1993). Depression and category learning, *Journal of Experimental Psychology General, 122*, 331-446.

Watson, D., Clark, L., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology, 54*, 1063–1070.