**The relationship between depressive symptoms, hypomanic symptoms, mood, and
category learning.**

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Abstract

Participants completed several self-assessments that measured depressive symptoms, hypomania, and mood. They were then asked to learn either a set of rule-based categories or a set of non-rule-based categories. Correlational analyses suggested that participants with high levels of self-reported depression were impaired on complex rule learning. In contrast, performance on a rule-based learning task was found to be improved by high levels of current positive mood. Multiple linear regression analyses further revealed that, when the variance due to other constructs was removed, the relationship between depressive symptoms and rule-based performance disappeared while the relationship between positive mood and rule-based performance remained significant. These findings suggest that positive mood is related to enhanced rule learning abilities. Neither level of depression nor positive mood were found to be related to performance on categories that could be learned via associative processes. This dissociation provides evidence for a dual systems approach to categorization. These findings also suggest that executive functioning impairments observed among individuals with depression may be specifically related to a lack of positive mood rather than overall depressive symptoms, per se. Stimuli, data, and analysis code is available at <https://osf.io/35pt6/>.

Keywords: category learning, depression, hypomania, mood

The relationship between depressive symptoms, hypomanic symptoms, mood, and category learning.

The influence of negative mood on cognitive processing has received considerable attention in the literature; however, many questions regarding the nature of these effects remain. Some research has suggested that negative mood narrows attentional focus. For instance, Tucker and colleagues (Derryberry & Tucker, 1994; Tucker & Williamson, 1984) reported that threatening situations constrict the scope of perceptual attention. Similarly, narrowed conceptual attention has been shown to be related to state and trait anxiety (Mikulincer, Kedem, & Paz, 1990; Mikulincer, Paz, & Kedem, 1990). Induced negative mood states have also been shown to promote a narrowed attentional focus in global-local response tasks: compared to neutral moods, negative moods have been found to be associated with more local-based classifications (Gasper & Clore, 2002) and slower responses to global trials (Baumann & Kuhl, 2005).

In contrast to the aforementioned studies, Gable and Harmon-Jones (2010) found that participants in a sad mood exhibited longer response times to local response trials in a global-local response task than participants in a neutral mood. Based on these findings, Gable and Harmon-Jones proposed that depression might broaden attention. In line with this hypothesis, von Hecker and Meiser (2005) observed that university students who reported high levels of current depressive symptoms were more accurate in recalling non-essential elements of a word recognition task than students with low levels of self-reported depressive symptoms. These findings suggest that depression may be associated with a less inhibited, defocused state of attention.

Additional research suggests that depression may also be related to impaired cognitive flexibility. For example, major depression has been linked with poor performance on the Wisconsin Card Sorting Task (Austin et al., 1992; Merriam, Thase, Haas, Keshavan, &

Sweeney, 1999). Furthermore, Smith, Tracy, and Murray (1993) reported that participants with higher than average self-reported depressive symptoms were impaired on a category learning task that benefited from a flexible, rule-based strategy; these participants were unimpaired on a task that could be learned via similarity.

Clearly, there is evidence for both the broadened and narrowed-attentional hypotheses. This paper seeks to contribute to the debate by addressing the question of whether self-reported depressive symptoms are related to better or worse performance on complex tasks that utilize executive functioning abilities, such as hypothesis testing and rule selection. Of particular interest is the relationship between depressive symptoms and cognitive flexibility. Cognitive flexibility plays a role in many everyday tasks, including categorization, problem solving, and decision making. If even moderate levels of depressive symptoms are related to impaired cognitive flexibility, this has implications for understanding academic performance in university populations and employee performance in the workplace.

The Category Learning Paradigm

To assess the relationship between depressive symptoms and cognitive performance, this study employed a category learning paradigm in which participants were asked to learn either rule-based (RB) or non-rule-based (NRB) categories. The selection of this paradigm was motivated by the COmpetition between Verbal and Implicit Systems (COVIS; Ashby, Alfonso-Reese, Turken, & Waldron, 1998) theory of category learning. This theory makes specific predictions regarding cognitive flexibility and the neuropsychology that underlies the learning of different types of categories.

According to COVIS, hypothesis testing is executed by a primary, explicit learning system that relies on working memory and executive control. COVIS also predicts the existence of a secondary, implicit learning system that employs associative processes to gradually learn procedural-based responses. The two systems compete during learning to

produce the correct response; they may also be viewed as complementary, with learning being shifted to the implicit system if the explicit system fails to provide satisfactory performance.

In RB categories, stimulus features are treated as separate dimensions. Consequently, a key aspect of RB categorization is that it relies on explicit reasoning processes and the abstraction of verbalizable rules. The complexity of these verbal rules can range from highly salient, unidimensional rules to more complex, multi-dimensional rules that require conjunctive or disjunctive reasoning. For participants to achieve high accuracy on an RB category-learning task, they must select and test rules that are held in working memory. If a rule does not lead to correct feedback, it is abandoned and new rules are tested. The use of a new rule requires one to switch attention away from the old rule so that a new rule can be selected.

Many NRB categories differ from RB categories in that category membership depends on the integration of multiple features. Learning NRB categories often relies on an information-integration strategy. In this type of strategy, a category is gradually acquired through reinforcement and repetitive stimulus-response pairings. As a result, it is often difficult to verbalize the strategy that is applied during the learning of NRB category sets. Given that RB categorization involves verbalizable rules and NRB categorization does not, RB and NRB categorization is proposed to rely primarily on the explicit and implicit learning systems, respectively (Ashby et al., 1998).

The Role of Cognitive Flexibility in Category Learning

Cognitive flexibility is a feature of executive functioning that supports diverse thinking and problem solving (Spiro, Coulson, Fletovich, & Anderson, 1994). For instance, cognitive flexibility helps one to make connections between concepts, develop an inventory of potential solutions, and overcome perseveration to switch responses when a solution is

incorrect or inappropriate for the situation. Due to its reliance on hypothesis testing and rule switching, the explicit learning system is believed to be more reliant on cognitive flexibility than the implicit learning system is. This conclusion is further supported by neurological research which suggests that cognitive flexibility is associated with brain regions such as the prefrontal cortex (PFC) but not with the basal ganglia (Barbey, Colom, & Grafman, 2013): areas that are also associated with the explicit and implicit systems, respectively (Ashby et al., 1998).

The connection between cognitive flexibility and explicit category learning is also reinforced by a series of studies examining RB and NRB category learning across the lifespan. For example, relative to adults, children are known to have shorter working memory spans, reduced executive functioning, and, as a result, less cognitive flexibility (Bayliss, Jarrold, Gunn, & Baddeley, 2003). Recent work in our lab has noted that, while children are generally able to learn RB and NRB categories, they struggle with RB categories relative to adults and show particular deficits on categories that are based on a complex, disjunctive rule (Minda, Desroches, & Church, 2008; Rabi, Miles, & Minda, 2015; Rabi & Minda, 2014). When working memory demands are reduced, however, children have been shown to perform as well as adults on complex rule learning tasks (Minda et al., 2008). Rabi and Minda (2014) subsequently linked these differences in RB category learning performance to developmental variations in executive functioning and working memory ability. In contrast, little if any difference was noted between children and adults when learning NRB categories defined by family resemblances. This finding is consistent with the idea that the learning of NRB categories is independent of working memory capacity.

Similar patterns of performance have been observed when comparing younger adults with older adults (Rabi & Minda, 2016, 2017). As with children, older adults sometimes struggle relative to younger adults with tasks that are dependent on working memory,

executive functioning, and cognitive flexibility. As such, older adults struggle to learn categories that depend on complex disjunctive rules, though they are able to learn simple, single dimensional rules and NRB family resemblance categories. Taken together, the work examining category learning across the lifespan implicates working memory capacity and executive functions as mediators of performance when learning RB categories but not NRB category learning.

Of particular relevance to this paper is work by Nadler, Rabi and Minda (2010) that found an association between positive mood and the learning of cognitive flexibility-dependent category sets. In their study, a positive, neutral, or negative mood was induced in participants prior to a category learning task. Participants in the positive mood condition demonstrated significantly better learning of an RB category set than participants in either of the other mood conditions. Negative mood induction produced non-significant reductions in performance but it was not clear if that induction was sufficient to affect learning. Furthermore, a negative mood induction is not the same as the hypothesised cognitive changes that are associated with depressive symptoms. In short, Nadler et al. (2010) confirmed the link between mood, cognitive flexibility, and category learning but their data were ambiguous about the effects of negative mood and depressive symptoms.

Subsequent research by Zivot, Cohen, and Kapacu (2013) found that, compared to an induced calm mood, an induced sad mood improved the performance of participants when learning RB categories but not family resemblance categories. Computational modelling on a second experiment suggested that a sad mood may have narrowed the attentional focus of participants: a finding that is consistent with other research on mood and cognition (e.g. Baumann & Kuhl, 2005; Gasper & Clore, 2002). Depending on how categories are defined and learned, however, a narrowed focus can either help or inhibit performance. If attentional focus is narrowed, some rules could be learned if they are straightforward and easy to

describe. In contrast, a narrowed attentional focus in conjunction with a reduction in cognitive flexibility may result in an inability to switch away from an incorrect rule if the correct rule is more complex.

In short, if depressive symptoms are related to narrowed attention and reduced flexibility, depressive symptoms should be negatively related to complex RB category learning performance. Early performance on NRB category learning may be affected by depressive symptoms if the explicit system is initially active. Overall, however, NRB categorization should be unaffected by a depression-related decline in cognitive flexibility.

The Role of Dopamine in Category Learning

Due to its reliance on associative learning processes, the implicit learning system is closely linked to the dopamine-reward system (Ashby et al., 1998). Feedback indicating a correct response will activate a neural reward signal in the form of dopamine travelling from the substantia nigra pars compacta to the tail of the caudate nucleus. Crucially though, the synapses between these structures are only active for several seconds. If corrective feedback and the reward signal are not received in a timely manner, the implicit system cannot make the proper connection between the categorization response and the feedback. Consequently, NRB learning is impaired when corrective feedback is not given immediately after participants make a response (Maddox, Ashby, & Bohil, 2003). Similarly, NRB learning may be compromised by decreased levels of dopamine in the tail of the caudate nucleus (Ashby et al., 1998; Knowlton, Mangels, & Squire, 1996).

Dopamine is also hypothesized to play a key role in the explicit system. COVIS suggests that the explicit learning system is mediated by a circuit that includes the PFC (involved in working memory and executive functioning), the anterior cingulate cortex (ACC; implicated in rule selection), and the head of the caudate nucleus (related to rule switching). Ashby et al. (1998) predict an inverse-U relationship between dopamine levels in

frontal brain regions and RB category learning: increased levels will enhance learning to a point but too much or too little dopamine hinders rule selection and subsequent performance.

The role of dopamine in category learning is important to consider in the context of this study because dopamine has also been implicated in theories of depression. In particular, low levels of dopamine within the mesolimbic dopamine pathway have been found to be associated with depressive behaviour (Nestler & Carlezon, 2006; Tye et al., 2013). This pathway projects from the ventral tegmental area (VTA) to the nucleus accumbens. This is significant because the VTA plays a role in the explicit learning system. According to COVIS, the ACC selects which new verbal rules to try and the head of the caudate nucleus controls rule switching. Dopamine projections between the VTA and substantia nigra mediate this switching process. Though dopamine is also implicated in implicit-based learning, the dopamine projections in this system are between the substantia nigra and the visual cortex (Maddox & Ashby, 2004). Depressive symptoms, therefore, should be related to RB category learning but not NRB category learning.

Despite the links between depression, dopamine, and RB categorization, little work has been done to specifically investigate the relationship between depressive symptoms and category learning. Smith and colleagues (1993) provide one of the few studies that addresses this area of research. In one experiment, university students were asked to complete the Beck Depression Inventory (BDI; Beck, 1967) and perform both RB and NRB category learning tasks. The stimuli for these tasks consisted of 4-letter non-words (e.g. BUNO, KYRA). Participants with higher than average BDI scores (i.e. scores that were greater than the mean score reported by all participants) performed poorer on the RB task than participants with lower than average scores. A second experiment involved a group of male veterans who were classified as non-depressed, moderately depressed, or severely depressed using the BDI recommended cut-off scores. These participants were asked to learn either an RB category set

or an NRB category set, both of which consisted of abstract faces with four features that varied along one of two dimensions. Participants classified as severely depressed were impaired on RB but not NRB category learning. No other group differences were observed.

The Present Research

The present research aims to extend previous work by considering a wider range of category sets, a wider range of depressive symptom assessments, and assessments of related mood and anxiety disorders. In particular, this study differs from previous research in five ways:

- 1) By using both simple and complex RB category sets, we provide an extensive test of the hypothesis that depressive symptoms are negatively related to RB category learning.
- 2) Though Smith et al. (1993) demonstrated that current self-reported depressive symptoms were related to poor RB category learning, other research has reported cognitive impairments in participants who are no longer depressed (Weiland-Fiedler et al., 2004). Therefore, to address the possibility that past depressive symptoms might be related to reduced RB category learning performance, we assessed participants' history of depressive symptoms in addition to their current depressive symptoms.
- 3) To the best of our knowledge, previous research has failed to adequately examine the possible relationship between category learning and mood disorders other than depression. Both depression and bipolar disorder are associated with frontal brain region dysfunction and working memory and executive function impairments (Arts, Jabben, Krabbendam, & van Os, 2008; Bora, Yucel, & Pantelis, 2009; Kurtz & Gerraty, 2009; Robinson et al., 2006). Given that hypomanic symptoms (i.e. persistent euphoric or irritable mood states; American Psychiatric Association, 2000) are a

predictor of bipolar disorder (Depue, Krauss, Spoont, & Arbisi, 1989), we predicted that hypomanic symptoms may be negatively related to RB category learning performance. Consequently, we assessed symptoms of hypomania.

- 4) Depression is related to a propensity for worrying (Fresco, Frankel, Mennin, Turk, & Heimberg, 2002; Starcevic, 1995) and worry has been found to hinder verbal working memory (Rapee, 1993). Dual-task category learning studies have reported that the addition of a verbal working memory task has a greater negative impact on RB learning than NRB learning (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). Thus, a tendency to worry may have similar interference effects on verbally-mediated category learning; we considered this possibility by accounting for proneness to worry.
- 5) Finally, depression is related to lower than usual approach motivation (Henriques & Davidson, 2000; Kasch, Rottenberg, Arnow, & Gotlib, 2002) and higher than usual avoidance motivation (Depue & Iacono, 1989; Kasch et al., 2002). Bipolar disorder has also been connected to approach motivation dysregulation (Alloy & Abramson, 2010). Therefore, we further examined whether or not approach and avoidance motivation is related to RB categorization performance.

Participants consisted of undergraduate students who reported a range of depressive symptoms but were not necessarily clinically depressed. The issue of whether high levels of depressive symptoms are comparable to ratings of clinical depression is contentious: some suggest that they are analogous (Vredenburg, Flett, & Krames, 1993) and others argue that they are qualitatively different (Gotlib, 1984). Nevertheless, we believe there is value in understanding how non-clinical depressive symptoms relate to category learning, specifically, and to cognitive processing in general.

Study 1

Study 1 was designed to investigate the relationship between self-reported depressive symptoms and RB and NRB category learning. We compared learning on two RB category sets: one that is similar to the stimuli used by Smith et al. (1993) in that it is relatively easy to learn using a single-dimensional verbal rule (i.e. an easy rule-based set; ERB), and a second, more complex task that requires the use of a disjunctive verbal rule (i.e. a hard rule-based set; HRB). We also employed an NRB category set that is relatively complex but can be learned without a verbal rule. These three category sets are similar to those examined in Zivot et al.'s Experiment 1 (2013). In addition to current level of depressive symptoms, we measured history of depressive symptoms, proneness to worry, current hypomanic symptoms, history of hypomanic symptoms, and approach and avoidance motivational strength.

We predicted that current depressive symptoms would be negatively related to HRB category learning but not NRB or ERB category learning. We did not anticipate a relationship between ERB category learning performance and depressive symptoms because a single-feature rule is easy to find and the process is less dependent on cognitive flexibility. In contrast, finding the optimal verbal rule for the HRB set requires a greater degree of flexibility and, thus, depressive symptoms should be negatively related to HRB performance. History of depressive symptoms, proneness to worry, hypomanic symptoms (past and present), and avoidance motivation were also expected to be negatively related to HRB category learning performance. Our predictions regarding approach motivation were less clear. It is possible that people who are sensitive to rewards will be more engaged during category learning than people lower in behavioural activation. An overactive reward system has, however, been linked to hypomanic symptoms (and bipolar disorder; Alloy & Abramson, 2010) and, as a result, it is possible that this relationship could be negative.

Method

Participants. Ninety undergraduate students (68 females) from the University of Western Ontario participated in this study. Participants received either \$10 or course credit for their participation.

Materials.

The Beck Depression Inventory-II. The Beck Depression Inventory-II (BDI-II; Beck, Steer, & Brown, 1996) is designed to evaluate the severity of current depressive symptoms in both psychiatric and normal populations. It consists of 21 items that assess features of depression (e.g. sadness, loss of pleasure, changes in sleep, etc.), with higher total scores indicating an increasing severity of symptoms. The BDI-II has a high level of internal consistency (Beck et al., 1996; Whisman, Perez, & Ramel, 2000), as well as good convergent and discriminant validity in college student populations (Dozois, Dobson, & Ahnberg, 1998; Steer & Clark, 1997; Whisman et al., 2000).

The General Behavior Inventory. The General Behavior Inventory (GBI; Depue, 1987) is a measure of bipolar and unipolar mood symptoms that was developed to assess minor mood disorders as well as major depressive and bipolar disorders (Akiskal, Khani, & Scott-Strauss, 1979; Reichart et al., 2005). The GBI is comprised of a 46-item depression scale (GBI-D) and a 27-item hypomania scale (GBI-H). Participants are asked to rate how frequently they have experienced a behaviour since they first noticed it across their lifetime, with higher total scores indicating a higher frequency. Many of the questions specify a minimum time range: for example, “Have there been times of *several days or more* [emphasis added] when you were so sad that it was quite painful or you felt that you couldn’t stand it?”

The Penn State Worry Questionnaire. The Penn State Worry Questionnaire (PSWQ; Meyer, Miller, Metzger, & Borkovec, 1990) is a 16-item questionnaire that assesses the

frequency and intensity of proneness to worry. Higher total scores on the PSWQ indicate a greater propensity to worry. This measure has good construct validity and internal consistency (Meyer et al., 1990; Molina & Borkovec, 1994).

Behavioral Inhibition System/Behavioral Activation System scale. The Behavioral Inhibition System/Behavioral Activation System (BIS/BAS; Carver & White, 1994) scale was designed to assess Gray's (1990) regulatory approach and avoidance systems. The 24-item measure contains four subscales: one that is BIS-related and three that are BAS-related.

The BIS is activated in response to environmental cues signaling punishment, novelty, and non-reward, and inhibits behaviour that could lead to aversive outcomes. This system has been argued to underlie negative affective feelings, including fear, sadness, and anxiety (Gray, 1990). High levels of BIS (indicated by high scores on the BIS subscale) have been connected to higher self-reports of depression symptoms (Hayden et al., 2008). The 7-item BIS subscale includes items designed to assess one's response to negative stimuli and events.

The BAS governs movement towards desired end states and is sensitive to cues signaling reward and non-punishment. This system has been argued to underlie positive affective states, including happiness and elation (Gray, 1990). The three BAS-related subscales focus on distinct aspects of sensitivity to rewards: drive (4 items), fun seeking (4 items), and reward responsiveness (5 items). The BAS subscales are often summed and used as an overall indicator of BAS sensitivity (e.g. Hayden et al., 2008; McFarland, Shankman, Tenke, Bruder, & Klein, 2006). Someone with a high BAS sensitivity (indicated by high scores on the BAS subscales) should experience a strong pull to engage in goal-directed behaviour and a strong reaction to impending incentives. Low BAS sensitivity, or an underactive BAS, has been found to relate to depression (Campbell-Sills, Liverant, & Brown, 2004; Fowles, 1988; Kasch et al., 2002; McFarland et al., 2006) and bipolar disorder (Meyer, Johnson, & Carver, 1999).

Hypomanic Personality Scale. The Hypomanic Personality Scale (HPS; Eckblad & Chapman, 1986) is a 48-item true/false measure that assesses features of hypomanic personality (e.g. elevated sociability, mood, energy, and perceived uniqueness). High scores on this measure are associated with increased rates of bipolar disorders and depressive episodes (Kwapil et al., 2000).

Category learning task. Three category learning sets (presented in Figure 1) were chosen from the original set of six created by Shepard, Hovland, and Jenkins (1961).¹ In each set there are eight stimuli that are divided equally between two categories. Each stimuli is characterized by three dichotomous features: shape (square or triangle), size (small or large), and color (blue or orange).

Figure 1. Category learning sets from Shepard, Hovland, and Jenkins (1961) used in Study 1: **(a)** easy rule-based (ERB), **(b)** hard rule-based (HRB), and **(c)** non-rule-based (NRB). Within each panel, items to the left of the line belong in the forest (i.e. Category A) and items to the right of the line belong in the mountains (i.e. Category B).

Easy rule-based. In the ERB category set (Type I in Shepard et al., 1961), category membership is determined by one of the three features. As a result, participants can achieve

perfect performance by using a single-dimensional verbal rule (e.g. in Figure 1a: “orange shapes belong in Category A, blue shapes belong in Category B”). Of the six category sets designed by Shepard et al., this set is the easiest to learn and results in the highest performance (Minda et al., 2008; Nosofsky, Gluck, Palmeri, Mckinley, & Glauthier, 1994; Rabi & Minda, 2016).

Hard rule-based. In the HRB category set (Type II in Shepard et al., 1961), category membership depends on two features. To achieve perfect performance, therefore, participants must use a disjunctive verbal rule (e.g. in Figure 1b: “blue triangles and orange squares belong in Category A, orange triangles and blue squares belong in Category B”). Thus, none of the features are individually helpful in assigning category membership but the combination of two features is. This set is the second easiest to learn out of Shepard et al.’s (1961) six category sets (Minda et al., 2008; Nosofsky et al., 1994; Rabi & Minda, 2016).

Non-rule-based. In the NRB category set (Type IV in Shepard et al., 1961), all three features are used to indicate category membership. This task is thought to be learned primarily via a family resemblance strategy. This means that the members of each category share the majority of their features with one another (e.g. in Figure 1c, the members of Category A are mostly large, orange, and/or triangular, whereas Category B members are mostly small, blue, and/or square). The NRB task, however, can also be thought of as a rule-plus-exception category learning task. Consequently, another possible method of achieving perfect performance with this set is to use a verbal rule that takes the exceptional outlying stimuli into account (e.g. in Figure 1c: “large shapes, except the blue square and plus the small orange triangle, belong in Category A; small shapes, except the orange triangle and plus the large blue square, belong in Category B”). Of Shepard et al.’s six category sets, this

set is the third hardest to learn and is equivalent in difficulty to Types III and V (Minda et al., 2008; Nosofsky et al., 1994; Rabi & Minda, 2016).

Procedure. Participants were tested in groups of up to four. After providing informed consent, participants completed the questionnaires via paper and pencil. Participants were then randomly assigned to one of the three category learning conditions (ERB, HRB, or NRB). The same procedure was used for all participants, regardless of condition.

Participants were told that they would be presented with abstract shapes and were required to classify them as either living in the forest (Category A) or the mountains (Category B). On each trial, a single stimulus was presented in the center of the computer screen. Participants were instructed to press the “1” or the “0” key to indicate whether the shape belonged in the forest or the mountains, respectively. After responding, participants were given corrective feedback: if the response was correct, the shape would smile and move towards the correct location on the screen; if the response was incorrect, the shape would first frown and move towards the incorrect location before smiling and moving to the correct location. Participants had unlimited time in which to make responses. This procedure was repeated for a total of 80 trials divided into ten repeating blocks of eight stimuli each. Stimuli were presented in a random order within each block and blocks were presented in an unbroken fashion. (Refer to Figure 2 for a visual depiction of the task procedure.)

Results

In all analyses, the BAS Total score is presented rather than the three BAS subscales; this reflects our interest in general BAS sensitivity as opposed to the specific constructs measured by each of the subscales. Also note that, due to experimenter error, BDI-II data is missing for eight participants in the ERB condition and three participants in the HRB condition. These 11 participants have been excluded from the analyses below. As a result, $n_{ERB} = 22$, $n_{HRB} = 27$, and $n_{NRB} = 30$.

Figure 2. Visual depiction of a correct (top) and incorrect (bottom) trial from the Study 1 categorization task. On correct trials, the stimulus smiles and moves to the selected (correct) location. On incorrect trials, the stimulus frowns and moves to the selected (incorrect) location before smiling and moving to the correct location.

Category learning performance. The learning curves of each category condition across all ten blocks of learning are shown in Figure 3.

A 3 x 10 mixed analysis of variance (ANOVA) was conducted with condition as a between-groups factor and block as a within-group factor.² The condition*block interaction was not found to be statistically significant; $F(16, 593) = 1.61, p = .064, \eta_p^2 = .04$. As expected, however, the main effects of block and condition were statistically significant; $F(8, 593) = 26.62, p < .001, \eta_p^2 = .26$ and $F(2, 76) = 16.24, p < .001, \eta_p^2 = .30$, respectively.

With respect to the main effect of block, Tukey HSD post hoc tests revealed that performance on block 1 was significantly lower than performance on all other blocks (for the comparison between blocks 1 and 2, $p = .03$; for all other block 1 comparisons, $p < .001$).

Figure 3. Proportion of category items responded to correctly by participants in the easy rule-based (ERB), hard rule-based (HRB), and non-rule-based (NRB) conditions across 10 blocks of learning. Error bars represent standard error of the mean (SEM).

Performance in block 2 was found to be significantly lower than performance in blocks 6 ($p = .02$), 7 ($p = .01$), 8 ($p = .001$), 9 ($p < .001$), and 10 ($p < .001$). Performance in block 3 was found to be significantly lower than performance in blocks 9 ($p = .02$) and 10 ($p = .03$). No other between-block performance comparisons were found to be significant (all $ps > .05$).

Tukey HSD post hocs further indicated that participants in the ERB condition performed significantly better on the category learning task than participants in both the HRB and NRB conditions (for both comparisons, $p < .001$). A significant performance difference was not observed between the NRB and HRB conditions ($p = .92$).

Scale reliability and descriptives. Reliabilities and descriptive statistics associated with each of the seven scales are presented in Table 1.

Correlations. Two-tailed Pearson correlations were performed to assess the relationship between overall performance on each of the three category sets (averaged across all ten blocks) and scores on each of the scales (presented in Table 2). A Bonferroni adjustment ($\alpha = .05/7 = .007$) was used to correct the family-wise error rate.

ERB. There were no significant correlations between any of the scales and overall performance on the ERB category set.

Table 1: *Scale reliabilities and descriptive statistics.*

Scale	α	ERB		HRB		NRB	
		<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Beck Depression Inventory-II	.89	11.82	8.27	9.78	6.25	10.30	8.12
General Behavior Inventory-Depression	.97	39.32	24.20	40.59	27.81	39.93	26.49
General Behavior Inventory-Hypomania	.92	23.00	10.61	25.85	12.85	21.80	14.99
Penn State Worry Questionnaire	.93	51.36	14.76	49.74	14.83	56.10	12.14
Behavioral Inhibition System	.83	21.09	3.50	20.22	4.34	20.33	5.18
Behavioral Activation System	.87	41.59	3.71	38.56	8.40	39.20	7.10
Hypomanic Personality Scale	.86	21.18	7.95	20.52	9.48	17.70	7.03

Notes: ERB = Easy Rule-Based, HRB = Hard Rule-Based, NRB = Non-Rule-Based.

Table 2: *Correlations between scale scores and overall category learning performance in each of the conditions.*

Scale	ERB		HRB		NRB	
	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>
Beck Depression Inventory-II	.08	.729	-.56	.002*	-.15	.420
General Behavior Inventory-Depression	-.17	.459	-.16	.416	-.49	.006*
General Behavior Inventory-Hypomania	-.27	.218	-.47	.013	-.41	.024
Penn State Worry Questionnaire	.05	.827	-.01	.956	-.30	.101
Behavioral Inhibition System	.02	.923	-.11	.581	-.06	.765
Behavioral Activation System	.10	.649	-.32	.108	.10	.587
Hypomanic Personality Scale	-.04	.860	-.17	.387	.005	.980

Notes: ERB = Easy Rule-Based, HRB = Hard Rule-Based, NRB = Non-Rule-Based. * $p \leq .007$.

HRB. Overall performance on the HRB category set was found to be negatively correlated with BDI-II scores. No other correlations were found to be significant.

NRB. Overall performance on the NRB category set was found to be negatively correlated with GBI-D scores. No other correlations were found to be significant.

Comparing correlations across conditions. Two-tailed comparisons ($\alpha = .05$) were conducted to determine whether the correlations between overall performance and each of the scales differed significantly from one another across conditions (Preacher, 2002; presented in Table 3).

Table 3: *Cross-condition comparisons between correlations.*

Scale	ERB-HRB		ERB-NRB		HRB-NRB	
	<i>z</i>	<i>p</i>	<i>z</i>	<i>p</i>	<i>z</i>	<i>p</i>
Beck Depression Inventory-II	2.33	.02*	0.78	.44	1.72	.09
General Behavior Inventory-Depression	0.01	.99	1.22	.22	1.31	.19
General Behavior Inventory-Hypomania	0.76	.45	0.52	.60	0.27	.79
Penn State Worry Questionnaire	0.20	.84	1.22	.22	1.08	.28
Behavioral Inhibition System	0.44	.66	0.26	.79	0.20	.85
Behavioral Activation System	1.40	.16	0.002	1.00	1.54	.12
Hypomanic Personality Scale	0.44	.66	0.15	.88	0.64	.52

Notes: ERB = Easy Rule-Based, HRB = Hard Rule-Based, NRB = Non-Rule-Based. * $p \leq .05$.

The performance/BDI-II score correlation was found to be significantly greater for the HRB condition than for the ERB condition. No other correlations were found to be significantly different from one another across conditions.

Regressions. As expected, several of the scales were significantly correlated with one another (intercorrelations are presented in Appendix A). To determine the proportion of variance in category learning performance that can be uniquely attributed to each scale, we conducted a series of multiple linear regressions with overall performance on each of the

category sets as separate dependent variables and scale scores as the predictor variables. All of the predictor variables were entered at the same time and all variables were mean-centered to insure against multicollinearity.

ERB. The multiple regression between scale scores and overall ERB performance did not reach significance; $R^2 = .16$, $R^2_{\text{adjusted}} = -.26$, $F(7, 14) = 0.39$, $p = .90$.

HRB. The multiple regression between scale scores and overall HRB performance was found to be significant, meaning that the linear combination of the seven scales was significantly related to performance on the HRB category set; $R^2 = .70$, $R^2_{\text{adjusted}} = .58$, $F(7, 19) = 6.22$, $p = .001$. Consistent with the results of the correlational analysis, the BDI-II ($\beta = -0.02$, $t = -4.88$, $p = .001$) was found to be a significant predictor of HRB performance. Unexpectedly, the regression analysis further revealed significant relationships between performance on the HRB category set and scores on both the GBI-H ($\beta = -0.01$, $t = -2.71$, $p = .01$) and the PSWQ ($\beta = 0.01$, $t = 2.77$, $p = .01$). No other predictor variables were found to be significantly related to HRB performance. Significance values for all predictors are presented in Table 4.

Table 4 also displays part correlations between overall HRB performance and each of the scales. Part correlations reflect the degree of relationship between the predictors and dependent variable when the variation that can be attributed to other predictors is removed from the predictor of interest. Because the dependent variable is not residualized, part correlations can be compared to one another and their squared value represents the proportion of variance in the dependent variable that is uniquely associated with each predictor (Cohen & Cohen, 1975). Squared part correlations suggest that the BDI-II, GBI-H, and PSWQ respectively account for 38%, 12%, and 12% of the variance in overall HRB performance.

Table 4: *Part correlations between scale scores and overall hard rule-based category learning performance.*

Scale	r_{part}	r^2_{part}	p
Beck Depression Inventory-II	-.62	.38	.001*
General Behavior Inventory-Depression	.26	.07	.06
General Behavior Inventory-Hypomania	-.34	.12	.01*
Penn State Worry Questionnaire	.35	.12	.01*
Behavioral Inhibition System	-.03	.001	.84
Behavioral Activation System	-.15	.02	.25
Hypomanic Personality Scale	.11	.01	.41

Notes: * $p \leq .05$.

NRB. Despite a significant correlation between NRB performance and GBI-D scores, the multiple regression between scale scores and overall NRB performance did not reach significance; $R^2 = .34$, $R^2_{\text{adjusted}} = .13$, $F(7, 22) = 1.59$, $p = .19$.

Discussion

The primary purpose of Study 1 was to investigate the relationship between current depressive symptoms and learning performance on three types of category sets. We predicted that BDI-II scores would be negatively related to HRB performance but unrelated to ERB and NRB performance. Correlational and multiple regression analyses confirmed these hypotheses. Impairments in complex RB learning, therefore, appear to be related to one's current level of depressive symptoms. A comparison of the BDI-II-related correlations between category types further revealed that this relationship between current depressive symptoms and HRB performance is significantly different than the relationship between current depressive symptoms and ERB performance; a significant difference between BDI-

II/HRB correlations and BDI-II/NRB correlations was only observed when a one-tailed test was implemented.

These results seem to contrast with Zivot et al.'s (2013) finding that sad mood improved performance on the same kinds of HRB categories considered in this study, though the possible process-oriented explanation (narrowed attentional focus) could be the same in both cases. For the HRB categories, a slightly narrower focus could restrict attention to the two diagnostic dimensions needed to learn the task. However, an even narrower focus, in combination with impaired cognitive flexibility, would restrict attention to a single dimension and would undermine performance on these categories because this category structure cannot be learned by attending to a single dimension.

In addition to current depressive symptoms, we considered several related factors, including history of depressive symptoms, proneness to worry, past and present hypomanic symptoms, and avoidance and approach motivation. Each of these variables, with the exception of approach motivation, were predicted to be negatively related to HRB performance. Unexpectedly, history of depressive symptoms was found to be negatively correlated with NRB performance. This relationship, however, does not appear to offer any predictive value as the multiple regression between questionnaire scores and NRB performance did not reach significance. Consistent with our predictions though, a multiple regression analysis suggested that history of hypomanic symptoms was significantly and negatively predictive of overall HRB performance. This result is in line with the hypothesis that hypomania could be related to impairments in executive functioning (Malhi et al., 2007), though neither history of hypomanic symptoms (measured via the GBI-H) nor symptoms of hypomanic personality (measured via the HPS) were found to be significantly correlated with performance on any of the category sets.

The only other variable that was found to be related to category learning performance was proneness to worry. In particular, a multiple regression analysis suggested that proneness to worry was significantly and positively related to HRB performance. Correlational analyses, on the other hand, did not reveal a significant relationship between proneness to worry and performance on any of the category learning tasks. These inconsistent and unanticipated results are difficult to interpret. It may be that proneness to worry served as a motivating factor that encouraged participants to perform as well as possible on HRB learning. Perhaps a more difficult RB category set would reveal the expected negative relationship between worry and performance; Study 2 aimed to address this potential issue by employing a different, more difficult RB task.

Study 2

Study 1 was motivated by previous work (Smith et al., 1993) demonstrating that participants with higher ratings of depressive symptoms are impaired on RB, but not NRB, category learning. Results from Study 1 partially supported these findings: current level of self-reported depression and history of hypomanic symptoms were found to be negatively related to performance on a complex RB task but unrelated to performance on a simple RB task. Interestingly, multiple regression analyses also suggested that complex RB performance is enhanced by proneness to worry; this result, however, was not confirmed by correlational analyses. Study 2 aimed to address this inconsistency by employing a different, more difficult RB task.

Another concern regarding Study 1 was that the NRB task could have been learned via a complex verbal rule. Furthermore, the relatively small number of learning trials (80) may not have been sufficient to allow participants to develop a nonverbal learning strategy. A secondary purpose of Study 2, therefore, was to address these potential issues by using an NRB category set that can only be learned well via nonverbal processes. Study 2 also

included a greater number of learning trials than Study 1. In addition to encouraging the development of a nonverbal strategy, the use of more trials allows us to look at potential differences between early versus overall learning.

Another major difference between Study 1 and Study 2 was the inclusion, in Study 2, of a measure of current mood state. This is in line with a suggestion by Watson, Clark, and Tellegen (1988) that, because depressive symptoms are affectively complex, it may be useful to distinguish between positive and negative mood states. It has further been suggested that, when used with non-clinical student populations, the BDI may reflect general distress or negative affectivity rather than depression (Gotlib, 1984). In line with this argument, we found strong, positive intercorrelations between some of the measures used in Study 1. Accounting for mood, therefore, will also help to determine the proportion of variance in performance that is unique to BDI-II scores.

Earlier work by Nadler and colleagues (2010) found a clear relationship between positive mood and RB category learning. However, prior research regarding negative mood has produced mixed results, with some studies demonstrating that negative mood narrows attention (Gasper & Clore, 2002) and others reporting null effects (Isen, Daubman, & Nowicki, 1987). Consequently, current negative mood may be either negatively related or unrelated to RB task performance. Positive mood, on the other hand, has been shown to enhance cognitive flexibility (e.g. Isen et al., 1987). As a result, we anticipated that we would find a positive relationship between positive affect and RB category learning performance. Positive affect is related to increased dopamine in frontal brain regions (Ashby et al., 1998; Depue & Collins, 1999). In contrast, depression is associated with a pattern of left frontal hypoactivation (Henriques & Davidson, 1991) and reduced dopamine in frontal brain regions (Tye et al., 2013). As a result, we again predicted that current depressive symptoms would be negatively related to RB category learning performance; however, it was

unclear whether this relationship would remain significant when mood was taken into account.

Method

Participants. Eighty-two undergraduate students (43 females) from the University of Western Ontario participated in this study. Participants received course credit for their participation.

Materials.

Positive And Negative Affect Schedule. The Positive And Negative Affect Schedule (PANAS; Watson et al., 1988) is a well-established measure of current positive and negative mood. Two 10-item subscales provide a measure of positive and negative affect, with higher scores on each scale indicating a higher level of corresponding mood.

Additional questionnaires. As in Study 1, Study 2 employed the BDI-II, the GBI, the PSWQ, and the BIS/BAS scale. The HPS, however, was not included in Study 2 because results from Study 1 suggested that category learning performance may be more strongly influenced by history of hypomanic symptoms than symptoms of hypomanic personality, specifically.

Category learning task. Stimuli for the category learning task consisted of sine-wave gratings that varied in spatial frequency and orientation. A total of 80 stimuli were generated for each category set (RB and NRB), with 40 stimuli in each category (Ashby & Gott, 1988; Zeithamova & Maddox, 2006). Stimuli were generated by randomly sampling 40 values from a multivariate normal distribution described by the parameters of each category. PsychoPy software (Pierce, 2007) was then used to generate sine wave gratings corresponding to each coordinate sampled from each distribution. Grating frequency was calculated as $f = .25 + (x_f/50)$ cycles per stimulus and orientation was calculated as $\theta = x_\theta(\pi/20)$ degrees. The resulting category structures for the RB and NRB category sets are illustrated in Figure 4.

Figure 4. Examples of the stimuli used in Study 2. Items from categories A and B are represented by the light and dark circles, respectively. The solid lines represent optimal decision boundaries between the two categories. **(a)** The distribution from which the rule-based (RB) category set was derived. Frequency is the critical attribute. **(b)** The distribution from which the non-rule-based (NRB) category set was derived. Category membership is dependent on both frequency and orientation.

The solid lines displayed in Figures 4a and 4b represent the optimal decision boundaries for the RB and NRB category sets, respectively. As depicted in Figure 4a, frequency is the critical attribute for the RB category set. In order to correctly classify the RB stimuli, therefore, participants need to respond according to a single-dimensional, frequency-based rule (e.g. “respond A if the stimulus has fewer than three stripes, otherwise respond B”) while simultaneously inhibiting attention to the more salient orientation dimension. As displayed in Figure 4b, the optimal decision boundary for the NRB category set lies diagonally within the distribution space. Consequently, both frequency and orientation must be considered together during categorization. This means that there is no easily verbalizable rule that allows for optimal NRB performance; instead, participants have to gradually learn to associate certain stimuli with certain responses.

Procedure. Participants were tested in groups of up to four. After providing informed consent, participants completed the questionnaires on a computer via the online survey tool, SurveyMonkey. Participants were then randomly assigned to one of the two category learning

conditions (RB or NRB). The same procedure was used for all participants, regardless of condition.

Participants were told that they would be presented with visual patterns and were required to classify them as either belonging to Category A or Category B. On each trial, a single stimulus was presented in the center of the computer screen. Participants were instructed to press the “1” or the “0” key to indicate whether the pattern belonged to Category A or Category B, respectively. After responding, participants were given corrective feedback: if the response was correct, participants saw the word “CORRECT” in green font; if the response was incorrect, participants saw the word “INCORRECT” in red font. Participants had unlimited time in which to make responses. This procedure was repeated for a total of 320 trials divided into four repeating blocks of 80 stimuli each. Stimuli were presented in a random order within each block and blocks were presented in an unbroken fashion. (Refer to Figure 5 for a visual depiction of the task procedure.)

Results

As in Study 1, the BAS Total score is presented rather than the three BAS subscales. Further note that, in the RB condition, one participant failed to complete the category learning task and three participants failed to complete all of the questionnaires. Questionnaire data is also incomplete for one participant in the NRB condition. These five participants have been excluded from the analyses below. As a result, $n_{RB} = 37$ and $n_{NRB} = 40$.

Category learning performance. The learning curves of the two category conditions across all four blocks of learning are shown in Figure 6.

A 2 x 4 mixed ANOVA was conducted with condition as a between-groups factor and block as a within-group factor.³ The condition*block interaction was found to be statistically significant; $F(3, 193) = 6.97$, $p < .001$, $\eta_p^2 = .09$. This significant interaction was further assessed via a test of simple main effects of block across condition. In particular, one-way

Figure 5. Visual depiction of a correct (top) and an incorrect (bottom) trial from the Study 2 categorization task. After identifying the stimuli as a member of Category A or B, participants were provided corrective feedback in the form of the word “CORRECT” or “INCORRECT.”

Figure 6. Proportion of category items responded to correctly by participants in the rule-based (RB) and non-rule-based (NRB) conditions across four blocks of learning. Error bars represent standard error of the mean (SEM).

ANOVA analyses were conducted to investigate the effect of block on category learning performance for each condition separately. A Bonferroni adjustment ($\alpha = .05/2 = .025$) was used when evaluating the main effects of each ANOVA.

With respect to the RB condition, a one-way ANOVA⁴ revealed a significant main effect of block; $F(2, 72) = 30.15, p < .001, \eta_p^2 = .46$. Tukey HSD post hoc tests indicate that RB performance on block 1 was significantly lower than performance on all other blocks (all $ps = .002$). No other between-block performance comparisons were found to be significant (all $ps > .05$).

With respect to the NRB condition, a one-way ANOVA revealed a significant main effect of block; $F(3, 117) = 3.43, p = .02, \eta_p^2 = .08$. Tukey HSD post hoc tests, however, found no significant between-block performance differences (all $ps > .05$).

The significant condition*block interaction appears to be driven by an increase in RB performance over time and a lack of change in NRB performance. RB performance rapidly improved between blocks 1 and 2 and subsequently reached a plateau where performance was maintained for the remainder of the task. This pattern of performance is consistent with participants quickly identifying a successful rule and continuing to use that rule throughout the duration of the task. NRB performance, on the other hand, remained low and any changes that occurred over time were subtle. These findings are in accordance with the idea that NRB category sets are more difficult to learn than RB category sets and that NRB learning is a slow and gradual process.

The early stages of an RB categorization task are unique in that it is during these early stages that learning really occurs. During the first block, participants must actively try to identify the correct strategy via rule selection and hypothesis testing. Once they have found the correct rule though, they can simply apply it to any new stimuli that they encounter. In an NRB categorization task, participants may also attempt to identify a rule during the early

stages of the task; upon failure to find an appropriate rule, however, participants must instead rely on associative-based learning strategies. Subsequent analyses in this study (i.e. correlational and regression-based analyses) will consider the potential effects that mood has on these initial stages of learning by assessing the relationship between scores on the mood scales and block 1 performance (in addition to overall performance).

Scale reliability and descriptives. Reliabilities and descriptive statistics associated with each of the eight scales are presented in Table 5.

Table 5: *Scale reliabilities and descriptive statistics.*

Scale	α	RB		NRB	
		M	SD	M	SD
Beck Depression Inventory-II	.91	9.62	6.97	10.63	9.26
General Behavior Inventory-Depression	.95	30.08	16.98	31.75	21.64
General Behavior Inventory-Hypomania	.90	19.70	10.21	18.73	10.92
Penn State Worry Questionnaire	.92	48.81	12.84	47.08	12.89
Behavioral Inhibition System	.59	20.76	2.88	20.35	2.89
Behavioral Activation System	.82	41.16	4.96	42.38	5.00
Positive and Negative Affect Schedule-Positive	.91	25.08	8.46	27.48	8.13
Positive and Negative Affect Schedule-Negative	.91	15.92	6.45	17.43	8.06

Notes: RB = Rule-Based, NRB = Non-Rule-Based.

Correlations. Two-tailed Pearson correlations were performed to assess the relationship between performance on each of the category sets (in both block 1 and averaged across all four blocks) and scores on each of the scales (presented in Table 6). A Bonferroni adjustment ($\alpha = .05/8 = .006$) was used to correct the family-wise error rate.

Table 6: *Correlations between scale scores and both block 1 and overall category learning performance in each of the conditions.*

Scale	Rule-Based				Non-Rule-Based			
	Block 1		Overall		Block 1		Overall	
	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>
BDI-II	-.54	.001*	-.47	.004*	-.06	.724	-.07	.652
GBI-Depression	-.38	.022	-.30	.072	-.002	.988	-.10	.552
GBI-Hypomania	-.31	.064	-.35	.034	.16	.312	-.05	.768
PSWQ	-.32	.051	-.22	.201	-.10	.547	-.16	.313
BIS	-.25	.131	-.14	.396	.10	.558	-.08	.608
BAS	.01	.953	-.04	.807	.21	.193	.08	.635
PANAS-Positive	.52	.001*	.43	.008	.20	.215	.28	.085
PANAS-Negative	-.12	.485	-.07	.660	.09	.585	.21	.202

Notes: BDI-II = Beck Depression Inventory-II, GBI = General Behavior Inventory, PSWQ = Penn State Worry Questionnaire, BIS = Behavioral Inhibition System, BAS = Behavioral Activation System, PANAS = Positive and Negative Affect Schedule. * $p \leq .006$.

RB. Both block 1 and overall RB performance were found to be negatively correlated with BDI-II scores. Block 1 RB performance was also found to be positively correlated with scores on the positive affect subscale of the PANAS questionnaire. No other correlations were found to be significant.

NRB. There were no significant correlations between any of the scales and either block 1 or overall NRB performance.

Comparing correlations between conditions. Two-tailed comparisons ($\alpha = .05$) were conducted to determine whether the correlations between both block 1 and overall performance and each of the scales differed significantly from one another across conditions (Preacher, 2002; presented in Table 7).

Table 7: *Cross-condition comparisons between correlations.*

Scale	Block 1 RB-NRB		Overall RB-NRB	
	<i>z</i>	<i>p</i>	<i>z</i>	<i>p</i>
Beck Depression Inventory-II	2.31	.02*	1.82	.07
General Behavior Inventory-Depression	1.65	.10	.89	.37
General Behavior Inventory-Hypomania	2.03	.04*	1.33	.18
Penn State Worry Questionnaire	1.00	.32	.23	.82
Behavioral Inhibition System	1.49	.14	.26	.80
Behavioral Activation System	.86	.39	.50	.62
Positive and Negative Affect Schedule-Positive	1.57	.12	.75	.46
Positive and Negative Affect Schedule-Negative	.88	.38	1.20	.23

Notes: RB = Rule-Based, NRB = Non-Rule-Based. * $p \leq .05$.

The correlations between block 1 performance and both BDI-II and GBI-H score were found to be significantly lower for the RB condition than for the NRB condition. No other correlations were found to be significantly different from one another across conditions.

Regressions. As in Study 1, several of the scales were significantly correlated with one another (intercorrelations are presented in Appendix B). To determine the proportion of variance in category learning performance that can be uniquely attributed to each scale, we conducted a series of multiple linear regressions with block 1 and overall performance on each of the category sets as dependent variables and scale scores as the predictor variables. All of the predictor variables were entered at the same time and all variables were mean-centered to insure against multicollinearity.

Block 1 RB. The multiple regression between scale scores and block 1 RB performance was found to be significant, meaning that the linear combination of the eight scales was significantly related to block 1 performance on the RB task; $R^2 = .55$, $R^2_{\text{adjusted}} =$

.42, $F(8, 28) = 4.21$, $p = .002$. Consistent with the results of the correlational analysis, the positive affect subscale of the PANAS questionnaire ($\beta = 0.01$, $t = 3.32$, $p = .003$) was found to be a significant predictor of block 1 RB performance. No other predictor variables were found to be significantly related to block 1 RB performance. Significance values for all predictors are presented in Table 8.

Table 8: *Part correlations between scale scores and block 1 rule-based category learning performance.*

Scale	r_{part}	r^2_{part}	p
Beck Depression Inventory-II	-.13	.02	.31
General Behavior Inventory-Depression	.09	.01	.50
General Behavior Inventory-Hypomania	-.21	.04	.11
Penn State Worry Questionnaire	.10	.01	.45
Behavioral Inhibition System	-.19	.03	.16
Behavioral Activation System	-.12	.01	.36
Positive and Negative Affect Schedule-Positive	.42	.18	.003*
Positive and Negative Affect Schedule-Negative	-.12	.01	.36

Notes: * $p \leq .05$.

Table 8 also displays part correlations between block 1 RB performance and each of the scales. Squared part correlations suggest that the positive affect subscale of the PANAS questionnaire accounts for 18% of the variance in block 1 RB performance.

Overall RB. The multiple regression between scale scores and overall RB performance was found to be significant, meaning that the linear combination of the eight scales was significantly related to overall performance on the RB task; $R^2 = .50$, $R^2_{\text{adjusted}} = .36$, $F(8, 28) = 3.49$, $p = .01$. Unexpectedly, both the GBI-H ($\beta = -0.01$, $t = -2.84$, $p = .01$) and the positive affect subscale of the PANAS questionnaire ($\beta = 0.01$, $t = 3.12$, $p = .004$) were found

to be significant predictors of overall RB performance. No other predictor variables were found to be significantly related to overall RB performance. Significance values for all predictors are presented in Table 9.

Table 9: *Part correlations between scale scores and overall rule-based category learning performance.*

Scale	r_{part}	r^2_{part}	p
Beck Depression Inventory-II	-.15	.02	.27
General Behavior Inventory-Depression	.22	.05	.11
General Behavior Inventory-Hypomania	-.38	.14	.01*
Penn State Worry Questionnaire	.10	.01	.48
Behavioral Inhibition System	-.07	.01	.60
Behavioral Activation System	-.09	.01	.53
Positive and Negative Affect Schedule-Positive	.42	.17	.004*
Positive and Negative Affect Schedule-Negative	.002	<.001	.99

Notes: * $p \leq .05$.

Table 9 also displays part correlations between overall RB performance and each of the scales. Squared part correlations suggest that the GBI-H and the positive affect subscale of the PANAS questionnaire respectively account for 14% and 17% of the variance in overall RB performance.

Block 1 NRB. The multiple regression between scale scores and block 1 NRB performance did not reach significance; $R^2 = .19$, $R^2_{\text{adjusted}} = -.02$, $F(8, 31) = .90$, $p = .53$.

Overall NRB. The multiple regression between scale scores and overall NRB performance did not reach significance; $R^2 = .21$, $R^2_{\text{adjusted}} = .01$, $F(8, 31) = 1.05$, $p = .42$.

Discussion

Study 2 sought to extend the results of Study 1 by using an RB category set that has previously been found to benefit from cognitive flexibility, as well as an NRB category set that can only be learned well via nonverbal processes and has not been found to benefit from cognitive flexibility (Maddox, Baldwin, & Markman, 2006). Due to the increased complexity of these category sets, Study 2 implemented more learning trials than Study 1. The inclusion of these additional trials also allowed for the examination of early versus overall learning. The final difference between Study 1 and Study 2 was the addition, in Study 2, of a measure of current positive and negative mood.

As in Study 1, we found a significant negative correlational relationship between current level of self-reported depressive symptoms and complex RB performance. This relationship was present in overall performance and was strongest in the first block of learning (which is equivalent in duration to the overall performance of Study 1). Despite these findings, results from the multiple linear regression revealed that BDI-II score was not significantly predictive of RB performance. We did, however, find a strong and significant relationship between self-reported positive affect and both block 1 and overall RB category learning. Regression analyses further revealed that a significant proportion of the variation in overall RB learning was also predicted by history of hypomanic symptoms.

No significant relationships were found to exist between NRB performance and any of the questionnaire scores. This is consistent with the results of Study 1 and is in line with the idea that RB and NRB category learning are governed by distinct learning systems (Ashby et al., 1998).

General Discussion

The key findings of this work are as follows:

- 1) Self-reported depressive symptoms are negatively related to complex RB category learning performance.
- 2) This relationship between depressive symptoms and RB performance *does not* remain significant when the variance that can be attributed to positive mood is accounted for.
- 3) Level of current positive mood is positively related to complex RB category learning performance.
- 4) This relationship between positive mood and RB performance *does* remain significant when the variance that can be attributed to other questionnaires/constructs is removed.

In showing that self-reported depressive symptoms are negatively related to RB category learning performance, Study 1 extends the results of Smith and colleagues (1993). Additionally though, Study 1 assessed several related constructs and found that history of hypomanic symptoms and propensity to worry were related to RB performance. This pattern of results, in conjunction with the work of Smith et al. (1993), seem to imply that mood has an impact on category learning and depressive symptoms are negatively related to RB category learning performance. This conclusion would be in line with the idea that major depression is related to impaired executive functioning. However, the results of Study 2 and the overall pattern of intercorrelations between questionnaires suggest that this inference may be premature.

In Study 2, when a multiple linear regression was performed with positive mood included, the effects of depressive symptoms were reduced below significance and only positive mood remained as a significant predictor of RB learning. Furthermore, current depressive symptoms were found to be positively correlated with both history of depressive symptoms and history of hypomanic symptoms. In light of the intercorrelations between these variables and the predictive power of current positive mood ratings, it is hard to argue

that the self-reports of depressive symptoms are measuring depression and not general psychological distress, as contended by Gotlib (1984).

Clark and Watson (1991) reported that the BDI seems to measure three components: general distress, low positive mood, and general somatic complaints. The finding that positive mood contributes more unique variance to RB category learning than depressive symptoms (that include a component of low positive mood) suggests that, in a general university population, the BDI-II might be assessing positive mood or, more specifically, a lack thereof. This is in line with the DSM-IV definition of depression which requires either elevated sad mood or a loss of pleasure/interest (i.e. anhedonia; American Psychiatric Association, 2000).

Our finding of a significant positive relationship between positive mood and early RB category learning is congruent with prior research showing that positive mood enhances cognitive flexibility (Ashby et al., 1998; Isen et al., 1987; Nadler et al., 2010). This result, in addition to a lack of any significant relationship between positive mood and NRB learning, is also consistent with the hypothesis that positive affect is related to increased dopamine in frontal brain regions (e.g. Ashby et al., 1998). Negative mood, in contrast, was not found to be significantly related to RB or NRB category learning performance.

In both Study 1 and 2, history of hypomanic symptoms significantly predicted complex RB performance. As in depression, the mesolimbic dopamine circuit has been implicated in theories of bipolar disorder (Cousins, Butts, & Young, 2009). As a result, it would not be surprising if history of hypomania and/or future risk of bipolar disorder is negatively related to complex RB category learning performance. Further research is needed to examine this potential relationship.

Studies 1 and 2 produced conflicting results regarding the relationship between proneness to worry and RB category learning. More specifically, Study 1 suggested that

proneness to worry is positively related to HRB performance while Study 2 found no relationship between proneness to worry and RB performance. Consequently, further work would also be useful in helping to clarify the nature of this relationship.

A key limitation to the generalizability of this work is the correlational nature of the studies. Although the correlations were theoretically motivated and the results were compelling, strong conclusions cannot be drawn. Future research should examine the influence of manipulated mood on category learning. In order to address whether clinical depression is related to impaired RB category learning, it will be necessary to use patients who have been identified as clinically depressed; this is something that has yet to be done.

In conclusion, depressive symptoms were found to be negatively correlated with complex RB category learning performance and negative mood ratings were unrelated to learning. In contrast, positive mood was positively related to RB learning and, when positive mood was included in a multiple regression with depressive symptoms, only positive mood significantly predicted performance. Complex rule learning and cognitive flexibility, therefore, seem to be specifically related to the presence or absence of positive mood.

Context Paragraph

Categorization allows individuals to organize the sensory world into meaningful, usable mental structures. As a result, the ability to categorize is fundamental for numerous aspects of cognitive functioning such as learning, problem solving, and decision making. It is valuable, therefore, to understand the ways in which categories are acquired and the various situational, developmental, and individual factors that may affect this acquisition process. This work, in particular, was designed to investigate the effects of mood and depressive symptoms on the category learning process. This topic is especially relevant given the high rates of depression, stress, and anxiety that are reported among Canadian post-secondary students (Chiose, 2016; Pfeffer, 2016): the group with which this research was conducted. This work suggests that these individuals (and others suffering from persistent mood disorders) may be impaired on complex rule learning due to low levels of positive mood. Further research on this topic is important for understanding the ways in which mood can help and/or hinder the learning process in both the school and workplace environment.

Author Note

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Ethics Statement

The research described in this manuscript was approved by the Research Ethics Board at the University of Western Ontario (<http://www.uwo.ca/research/services/ethics/index.html>). The research complies with APA ethical standards as well as the ethical guidelines set by the Canadian TCPS2 (<http://www.pre.ethics.gc.ca/eng/policy-politique/initiatives/tcps2-eptc2/Default/>).

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Footnotes

¹ Shepard et al. (1961) created six category sets and ordered them according to difficulty (e.g. Type I, Type II...Type VI), although some category structures were equivalent in difficulty (Type III, IV, and V).

² Mauchley's sphericity test indicated a violation of sphericity for both the main effect of block and the condition*block interaction; for both, $W = .30, p < .001$. Girden (1992) suggests that a Greenhouse-Geisser correction should be applied when $\epsilon < .75$ but that when $\epsilon > .75$, a Huynh-Feldt correction is more appropriate. In this case, $\epsilon > .75$; therefore, a Huynh-Feldt correction ($\epsilon = .87$) has been applied to these effects.

³ Mauchley's sphericity test indicated a violation of sphericity for both the main effect of block and the condition*block interaction; for both, $W = .74, p < .001$. Because $\epsilon > .75$, a Huynh-Feldt correction ($\epsilon = .86$) has been applied to these effects. Note, however, that because the interaction effect was significant, the main effect of block is not discussed further.

⁴ Mauchley's sphericity test indicated a violation of sphericity for the main effect of block; $W = .44, p < .001$. Because $\epsilon < .75$, a Greenhouse-Geisser correction ($\epsilon = .67$) has been applied to this effect.

Appendix A

Table 10

Study 1 scale intercorrelations for participants in the easy rule-based condition.

	BDI-II		GBI-D		GBI-H		PSWQ		BIS		BAS	
	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>
BDI-II												
GBI-D	.68*	.001										
GBI-H	.21	.348	.66*	.001								
PSWQ	.49	.021	.20	.362	-.05	.832						
BIS	.36	.100	.26	.251	-.02	.932	.74*	< .001				
BAS	-.10	.672	.02	.926	.19	.388	-.18	.424	.06	.785		
HPS	-.14	.522	.12	.610	.62*	.002	-.18	.426	-.16	.483	.39	.069

Notes: BDI-II = Beck Depression Inventory-II, GBI-D = General Behavior Inventory-Depression, GBI-H = General Behavior Inventory-Hypomania, PSWQ = Penn State Worry Questionnaire, BIS = Behavioral Inhibition System, BAS = Behavioral Activation System, HPS = Hypomanic Personality Scale. * $p \leq .007$.

Table 11

Study 1 scale intercorrelations for participants in the hard rule-based condition.

	BDI-II		GBI-D		GBI-H		PSWQ		BIS		BAS	
	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>
BDI-II												
GBI-D	.45	.018										
GBI-H	.31	.116	.65*	< .001								
PSWQ	.61*	.001	.45	.019	.21	.292						
BIS	.46	.015	.45	.018	.27	.171	.62*	.001				
BAS	.33	.098	.29	.148	.38	.047	.41	.032	.35	.076		
HPS	-.06	.765	-.04	.850	.43	.026	-.12	.555	.01	.964	.16	.420

Notes: BDI-II = Beck Depression Inventory-II, GBI-D = General Behavior Inventory-Depression, GBI-H = General Behavior Inventory-Hypomania, PSWQ = Penn State Worry Questionnaire, BIS = Behavioral Inhibition System, BAS = Behavioral Activation System, HPS = Hypomanic Personality Scale. * $p \leq .007$.

Table 12

Study 1 scale intercorrelations for participants in the non-rule-based condition.

	BDI-II		GBI-D		GBI-H		PSWQ		BIS		BAS	
	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>
BDI-II												
GBI-D	.55*	.002										
GBI-H	.21	.262	.76*	< .001								
PSWQ	.23	.222	.33	.071	.32	.084						
BIS	-.05	.780	-.05	.777	.17	.366	.28	.132				
BAS	-.06	.735	.04	.846	.29	.116	-.11	.560	.68*	< .001		
HPS	-.06	.758	-.01	.946	.36	.054	.08	.664	.21	.276	.37	.043

Notes: BDI-II = Beck Depression Inventory-II, GBI-D = General Behavior Inventory-Depression, GBI-H = General Behavior Inventory-Hypomania, PSWQ = Penn State Worry Questionnaire, BIS = Behavioral Inhibition System, BAS = Behavioral Activation System, HPS = Hypomanic Personality Scale. * $p \leq .007$.

Appendix B

Table 13

Study 2 scale intercorrelations for participants in the rule-based condition.

	BDI-II		GBI-D		GBI-H		PSWQ		BIS		BAS		PANAS-P	
	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>
BDI-II														
GBI-D	.70	< .001*												
GBI-H	.52	.001*	.78	< .001*										
PSWQ	.39	.017	.41	.011	.35	.036								
BIS	.01	.938	-.13	.457	-.16	.332	.51	.001*						
BAS	-.14	.405	-.18	.287	.15	.379	.08	.639	.03	.878				
PANAS-P	-.37	.026	-.16	.334	.21	.216	-.22	.200	-.27	.100	.36	.030		
PANAS-N	.44	.007	.54	.001*	.63	< .001*	.17	.322	-.42	.009	.05	.789	.32	.055

Notes: BDI-II = Beck Depression Inventory-II, GBI-D = General Behavior Inventory-Depression, GBI-H = General Behavior Inventory-Hypomania, PSWQ = Penn State Worry Questionnaire, BIS = Behavioral Inhibition System, BAS = Behavioral Activation System, PANAS-P = Positive and Negative Affect Schedule-Positive, PANAS-N = Positive and Negative Affect Schedule-Negative. * $p \leq .006$.

Table 14

Study 2 scale intercorrelations for participants in the non-rule-based condition.

	BDI-II		GBI-D		GBI-H		PSWQ		BIS		BAS		PANAS-P	
	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>	<i>r</i>	<i>p</i>
BDI-II														
GBI-D	.85	< .001*												
GBI-H	.69	< .001*	.83	< .001*										
PSWQ	.56	< .001*	.52	.001*	.44	.005*								
BIS	.30	.062	.33	.037	.30	.057	.47	.003*						
BAS	-.03	.835	-.01	.947	.19	.247	.07	.650	-.08	.645				
PANAS-P	-.04	.806	-.05	.742	.10	.530	.18	.263	-.08	.646	.15	.345		
PANAS-N	.68	< .001*	.63	< .001*	.52	.001*	.46	.003*	.27	.092	-.04	.829	.28	.079

Notes: BDI-II = Beck Depression Inventory-II, GBI-D = General Behavior Inventory-Depression, GBI-H = General Behavior Inventory-Hypomania, PSWQ = Penn State Worry Questionnaire, BIS = Behavioral Inhibition System, BAS = Behavioral Activation System, PANAS-P = Positive and Negative Affect Schedule-Positive, PANAS-N = Positive and Negative Affect Schedule-Negative. * $p \leq .006$.