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Model-based learning and individual differences in depression: The moderating role of stress

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ABSTRACT

Inflexible decision-making has been proposed as a transdiagnostic risk factor for mood disorders. Evidence suggests that inflexible decision-making may emerge only when individuals are experiencing increased negative affect or stress. 151 participants completed symptom measures of depression and anxiety, followed by a two-stage decision-making task that distinguishes between habitual and goal-directed choice. An experimental manipulation to induce stress was introduced halfway through the task. Individuals with higher depression levels became less model-based after the manipulation than those with lower depression levels. There was no relationship between trait anxiety and the impact of the manipulation on decision-making. Controlling for main effects of anxiety did not attenuate the association between depression and impact of stress. Anhedonia was associated with the impact of the manipulation on model-based decision-making. These results suggest that risk for depression is associated with reflexive decision-making, but these effects may only emerge under conditions of stress.

1. Introduction

Learning to select actions that lead to the best possible outcomes is critical for successfully navigating one's environment and self-regulation. A number of theories suggest separable valuation systems that support this type of decision making, by working in concert to adaptively respond to external cues. Typically, these systems are characterized as a reflexive or habitual decision making mode, versus a deliberative or controlled decision making mode (Balleine & O'Doherty, 2009; Dolan & Dayan, 2013). Should one or the other system dominate, decision-making can become impaired, resulting in an inability to respond flexibly to one's environment. In particular, it has been suggested that in certain psychopathologies the reflexive/habitual system may dominate, which may help account for self-regulatory deficits noted across the internalizing spectrum (Huys, Guitart-Masip, Dolan, & Dayan, 2015b).

Recently, experimental tasks have been developed that are inspired by computational theories of reinforcement-learning to capture the degree to which individuals engage in model-free or model-based decision making (Daw, Niv, & Dayan, 2009). These tasks are designed to distinguish whether an individual tends to engage the more reflexive/habitual decision making mode, or the more deliberative/controlled decision making mode (Daw, Gershman, Seymour, Dayan, & Dolan, 2011). Model-free decision-making relies primarily on the most recent trial-and-error feedback to inform future decisions. In this learning strategy, current choices are based only on recent reinforcement, but require less control from the central executive, are more automatic, and inflexible. In contrast, model-based decision making functions via a flexible and more computationally demanding process, in which one creates and utilizes a cognitive 'model' of the transitions and outcomes in the external environment to prospectively plan choices. At the same time, this comes at a computational cost and accordingly places large demands upon central executive processing (Otto, Gershman, Markman, & Daw, 2013a).

However, the majority of model-based/model-free decision making studies have not examined how situational, affective factors such as current affective state or stress interact with trait factors such as depression risk to clarify how decisions are made. Everyday decision making does not function in a vacuum, and we are often required to make decisions in various emotional states (Dunn, Dalgleish, & Lawrence, 2006). Increases in negative affect or acute stress often engenders reliance on more automatic and habitual processes in human decision making (Starcke & Brand, 2012), perhaps via mechanisms that impair central executive functioning (Masicampo & Baumeister, 2008; Otto, Raio, Chiang, Phelps, & Daw, 2013b; Putman, Hermans, & van Honk, 2010). Experimental psychopathology research similarly

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indicates that decision making of individuals at risk for mood disorders are often more sensitive to the effects of increased negative affect and acute stress (Miu, Heilman, & Houser, 2008). Thus, a key additional feature of decision-making is that individuals at higher risk for depression may be particularly prone to less adaptive decision-making when experiencing heightened negative affect and stress. This hypothesis would suggest that while in a neutral state, individuals with vulnerabilities to mood disorders may show similar decision making profiles as their less susceptible peers, but that following circumstances that increase negative affect or stress, vulnerable individuals may demonstrate greater reflexive and/or habitual decision making.

The extant research on model-free/model-based decision making that has examined individual differences in risk for psychopathology has primarily focused on specific diagnostic syndromes, such as depression or trait anxiety (Gillan, Kosinski, Whelan, Phelps, & Daw, 2016), disorders of compulsion (Voon et al., 2015), eating disorders (Reiter, Heinze, Schlagenhauf, & Deserno, 2017), or addiction (Sebold et al., 2014), although evidence has been mixed (Reiter, Deserno, Wilbertz, Heinze, & Schlagenhauf, 2016; Sebold et al., 2017; Voon, Reiter, Sebold, & Groman, 2017). Other research has examined the relative contributions of model-based/model-free decision-making as a function of traits linked with psychopathology, including impulsivity (Deserno et al., 2015; Reiter et al., 2016), accumulated real-life stress (Friedel et al., 2017), and habit formation (Gillan, Otto, Phelps, & Daw, 2015). This literature has tended to not consider whether and how stress experienced during the task may interact with the individual differences in question. One notable exception was a study by Radenbach et al. (2015), which examined associations between model-based behavior and lifetime stress finding that change in model-based behavior following an acute stress induction was associated with greater lifetime stress. A second consideration characterizing the recent literature on model-free/based behavior is that the majority of studies (see: Gillan et al., 2016) have considered singular symptom-based phenotypes. Interestingly, Gillan et al. found that deficits in model-based decision making was most strongly associated with symptoms of obsessive compulsive behavior, eating disorders and substance abuse, (together termed "compulsive behavior and intrusive thought") but were not at all associated with individual differences in severity of mood symptoms.

Thus, despite the clear benefit of using traditional diagnostic classifications, there is substantial comorbidity between many mood and anxiety disorders (Kessler, Chiu, Demler, Merikangas, & Walters, 2005). The frequent overlap between mood and anxiety disorders raises the question of whether there are decision-making factors that are specific to one or the other disorder, or whether decision-making difficulties play a role as shared etiological factor across classic diagnostic boundaries. With respect to the current investigation, examining relationships across different symptoms can help map which processes most strongly predict susceptibility towards more reflexive or habitual decision making when stress or negative affect is increased. Such an approach concurs with recent recommendations to consider transdiagnostic factors (Cuthbert & Kozak, 2013), while also more accurately reflecting the relationship between mood and anxiety disorders (Eaton et al., 2013; Haslam, Holland, & Kuppens, 2012; Wright et al., 2013). There is compelling evidence, for example, that negative cognitions are common to mood and anxiety disorders and may be the psychological explanation for the high rates of comorbidity between mood and anxiety disorders (Mineka, Watson, & Clark, 1998). Anhedonia, on the other hand, is thought to be specific to depression and uniquely associated with the depressive phenotype (Brown, Chorpita, & Barlow, 1998).

The current study examined whether individual differences in mood and anxiety symptoms are associated with decision making before and after an experimental manipulation designed to induce stress. Participants completed lab-based measures of mood and anxiety symptom severity, followed by a two-stage decision making task that has been used extensively to assess and individuals' relative reliance on model-based versus model-free control (Daw et al., 2011; Gillan et al., 2016; Otto, Raio, Chiang, Phelps, & Daw, 2013b). Halfway through the choice task, participants were told that each had a 50% probability of being selected to give a speech at the end of the task to support their position on a politically charged topic that would be assigned to them by the experimenter. This task was similar to the Trier Social Stress Test (Kirschbaum, Pirke, & Hellhammer, 1993).[1] The second half of the model-based/model-free decision making task was therefore completed under the anticipatory state of knowing that one might be required to give a speech. In addition, although, this task did not have a control group not experiencing a manipulation, a noted limitation of this design, our interests were specifically on individual differences in decision making in response to this manipulation.

We first tested whether individuals higher in measures of depression and anxiety, would be more susceptible to become less model-based in their decision-making, before vs. after the manipulation. Because anhedonia has been hypothesized to be specific to depression (Clark & Watson, 1991), to test the specificity of these effects, we examined whether individual differences in anhedonia would be associated with susceptibility to become more reflexive in decision-making following the stressor.

2. Methods

2.1. Participants

The sample was collected across three waves over two semesters and consisted of 151 young adults (99 female; 81 White Non-Hispanic, 27 White Hispanic, 21 African American, 22 Asian; mean age = 19.54 years; sd = 2.12) who completed the in-lab behavioral task. Participants were provided with research familiarization credit as part of an Introduction to Psychology course at the University of Miami. There were no specific inclusion or exclusion criteria. All participants provided written informed consent according to the procedures of the institutional review board.

2.2. Self-report measures of trait negative and positive affect

Depression Severity. Depression severity was measured using the Patient Health Questionnaire-9 (PHQ-9; Spitzer, Kroenke, & Williams, 1999). The PHQ-9 is a nine-item self-report scale of depression asking participants to report, "Over the last 2 weeks, how often have you been bothered by any of the following problems". On a 0–3 scale, participants rate their level of difficulty on various symptoms associated with depression such things as, "interest or pleasure in doing things", "feeling down or hopeless", "little energy", and "trouble concentrating" among others. Test-retest reliability has been reported as 0.86 (Spitzer et al., 1999). It has been suggested that a PHQ-9 10 or greater are 6.0 times more likely to have a diagnosable depressive disorder than below 10. In this sample, 25 participants had a PHQ-9 score greater than or equal to 10. Overall, mean PHQ-9 depression severity was 4.88 (sd = 4.11, min = 0, max = 22) in this sample with an internal consistency of $\alpha = 0.809$.

Trait Anxiety. Trait anxiety was measured using the State-Trait Anxiety Inventory (STAI; Spielberger, Gorsuch, Luschene, Vagg, & Jacobs, 1983). The STAI is a 20-item measure of trait anxiety focused on areas including: worry, tension, apprehension, and nervousness. Internal consistency coefficients for the scale have ranged from 0.86 to

[1] Although we utilized a manipulation typically associated with "stress", we did not measure cortisol, an objective measure of stress. However we do demonstrate that there were increases in negative affect (NA). In the absence of a physiological measure of the stress response, we note that we refer to this manipulation as a stressor cautiously.

0.95 while test-retest reliability coefficients have ranged from 0.65 to 0.75 over a 2-month interval (Spielberger et al., 1983). Mean STAI was 41.93 (sd = 9.90, min = 23, max = 74) in this sample with an internal consistency ofα = 0.912.

Anhedonia. Individual differences in anhedonia were measured using the Snaith Hamilton Pleasure Scale (SHAPS; Snaith et al., 1995). SHAPS is a 14-itme measure of anhedonia asking participants to rate on a 4 point-scale (Strongly disagree to strongly agree) their level of enjoyment of various domains including, "enjoying being with family/friends", "pleasure in hobbies", "enjoying favorite meal", etc. Internal consistency of the SHAPS has been found to be quite high with alphas around 0.91. Mean SHAPS was 0.83, (sd = 1.46, min = 0, max = 8) in this sample with an internal consistency of α = 0.709.

2.3. Reinforcement-learning task

We utilized an adapted sequential learning task from Daw and colleagues (Daw et al., 2011; Decker, Otto, Daw, & Hartley, 2016; Potter, Bryce, & Hartley, 2016). Participants were typically run in groups of 4 at separate computer workstations in the same room, but some participants were run in smaller groups. Participants received instructions on the task structure and they completed practice trials prior to performing the task. At the start of each trial, a forced choice with two alternatives was presented. Participants chose between one of two spaceships that led, probabilistically, to one of two planets. Each spaceship traveled more frequently to one planet than to the other (70% versus 30%). For example, the blue spaceship had a 70% probability of leading to the red planet (the common transition) and a 30% probability of leading to the purple planet (the rare transition). The green spaceship had the opposite probabilities. On each planet, participants chose between two alien-creature stimuli (second-stage choice). They were then rewarded with a picture of space treasure or with nothing (an empty circle). The reward probabilities associated with second-stage actions were governed by independent, slowly-drifting Gaussian random walks (sd = 0.025) with reflecting boundaries at 0.25 and 0.75. Participants were given 3 s to make each choice, followed by a 1-s animation, 1 s of reward feedback, and then a 1-s inter-trial interval.

First-stage choice behavior is predicted to vary as a function of reward and transition history. In the idealized example, a completely model-free learner will select the same first stage choice (the spaceship) if the previous trial was rewarded, regardless of whether the previous first stage transition was common (70%) or uncommon (30%). As such, this model-free learner follows what previously happened, ignoring the overall transition structure. In contrast, a model-based learner takes into account both reward history and transition structure and thus shows a reward × transition interaction with a decreased likelihood of repeating the same first-stage choice if it had led to a reward via an uncommon transition.

2.4. Stress induction

Halfway through the experiment (after 75 of the trials), there was a brief break in the game and participants were presented with a stressor derived from the Trier Social Stress Task (Kirschbaum et al., 1993). Specifically, participants were told that following the game, 50% of the participants would be selected at random to give a speech. Participants were further told that individuals selected to give the speech would have 2 min to prepare, and then 5 min to perform the speech. This speech would present an argument supporting their position on the randomly assigned topic of the death penalty, the Black Lives Matter movement, or abortion. Rather than providing an emotional argument or opinion, participants were told that they should provide a scientific argument supporting their position. Participants were further told that their speech would be evaluated according to flow, eloquence, and sophistication of word choice and would be videotaped so a panel of your peers can rate the strength of their argument. After receiving this set of instructions, participants then continued with the task and completed another 75 trials in the sequential learning task. Altogether, participants completed 150 trials. The random walk procedure was the same as used by Daw et al. (2011). In short, a Gaussian random walk governed the probability with which second-stage choices were rewarded. Thus, after each trial the probability that a specific second-stage choice will be rewarded is not fixed but changes over time. This is done to ensure that participants need for continually update (i.e. learn) the values of first- and second-stage actions. After completing the task participants were notified if they would have to give the speech. Participants not selected departed at that point, while the remaining participants stayed and delivered a short speech.[2]

For a subset of participants (n = 78), individuals were asked to rate their current emotional state five different times during the two-step decision-making task. On the screen, a pause was inserted into the task and participants rated their current affect using a bipolar (negative to positive) visual analog scale on a sheet of paper. Affect was rated before the beginning of the task, a quarter of the way through the task (after 37 trials), before the introduction of the speech (after 75 trials), after the introduction of the speech (also after 75 trials), three-quarters of the way through the task (after 112 trials) and at the end of the task. These self-report data were only collected for participants in the third cohort of data collection which is why not all participants have self-report affect data.

2.5. Task data analysis

We assessed the relative contributions of model-based and model-free learning as a function of depression severity, anxiety severity and daily negative affect, both before and after the stressor. Our a-priori hypotheses specifically focused on the 4-way interactions (one for depression and one for anxiety, pre vs. post negative stressor). To do this, we analyzed the choice behavior using a linear mixed effects logistic regression with the lme4 R-package. The mixed-effects logistic regression was used to examine whether the participant selected the same or different first stage option (the spaceship) based on the previous trial's reward, transition type and whether it occurred prior to or following the stressor. The dependent variable was the first-stage choice (stay or shift, coded 0/1). Predictors included dummy variables indicating whether the previous trial was rewarded or not, whether the previous trial's transition was rare or common, whether the trial was before or after the introduction of the speech (the stressor; all coded −1/1), individual differences in depression severity (PHQ-9; z-scored between subjects) as well as all possible resultant interaction terms. An additional covariate included a dichotomous factor corresponding to which wave of data collection the participant was part of. The multilevel models included random effects for whether the previous trial was a win or loss, whether the last trial was characterized by a common or uncommon transition, whether the trial was before or following the stressor, and the term in which the data were collected. In separate models, we performed additional tests utilizing the STAI and SHAPS with identical predictors. We performed several analyses addressing specificity, including ones where we analyzed only the first half of the trials (i.e., prior to the stressor). In these analyses, we removed manipulation as a predictor.

All coefficients were taken as random effects across participants, and estimates are reported across participants.

[2] As the goal of this project was to examine the effect of a stressor on individual differences in model-based decision making, the speech content and performance was not relevant to the current study. However, so as not to deceive participants, performing the speech was in fact required of half the participants.

3. Results

3.1. Correlations between self-report measures

There were significant associations between the PHQ-9, STAI-Trait and SHAPS. The correlation between PHQ-9 and the STAI was significant ($r(150) = 0.69$, $p < 0.001$. The correlation between the PHQ-9 and the SHAPS was also significant ($r(150) = 0.39$, $p < 0.001$). And lastly, the correlation between the STAI and SHAPS was significant ($r(150) = 0.36$, $p < 0.001$).

3.2. Change in affect pre to post negative stressor

For a subset of participants (78 of the total sample), affect ratings using a visual analog scale were collected at various points throughout the two-step decision-making task. As part of this procedure, affect ratings were collected immediately before and after the stressor as a check to confirm that the manipulation had its intended effect. There was a significant change in self-reported affect from pre-to post-manipulation in the anticipated, negative direction ($t(77) = -5.68$, $p < 0.001$) indicating that the experimental manipulation indeed substantially increased negative affect. Importantly, the manipulation did not exert a stronger effect for individuals high in depression compared to individuals low in depression ($r = -0.01$, $p = 0.93$), indicating that the stressor impacted all participants roughly equally, regardless of risk for depression. Similar results emerged when we considered anxiety ($r = 0.05$, $p = 0.69$).

3.3. Main effects of change in decision-making

We conducted a mixed-effects logistic regression analysis to test whether there was a significant change in model-based decision making attributable to the stressor irrespective of individual differences in depression or anxiety. First, there was a main effect of reward ($B = 0.45$, $p < 0.001$) on first stage choice, indicating that individuals repeated their first-stage spaceship choice more often if the previous trial was rewarded. There was also a significant main effect of the manipulation on first stage choice such that individuals were more likely to stay with the same first stage choice after the stressor as compared with before the stressor ($B = 0.14$, $p < 0.001$). There was also a significant reward × transition interaction ($B = 0.21$, $p < 0.001$), denoting that subjects stayed more often after common trials, when they were rewarded and stayed after rare trials when they were not rewarded. There was also a significant Transition x Pre/Post-Stressor interaction ($B = -0.050$, $p = 0.03$). There was no significant Reward x Transition × Stressor interaction ($B = -0.02$, $p = 0.43$) indicating that the stressor did not significantly impact model-based decision making for all participants. That said, the lack of a control group not experiencing the manipulation is worth noting as it is impossible to completely rule out the possibility that time on task was a contributing factor to these results.

3.4. Change in model-based decision making & depression levels

We conducted a mixed-effects logistic regression analysis to test whether there was an interaction between self-reported depression severity and change in model-based decision making attributable to the stressor (Table 1). First, there was a main effect of reward ($B = 0.52$, $p < 0.001$) on first stage choice, indicating that individuals repeated their first-stage spaceship choice more often if the previous trial was rewarded. There was a significant effect of the stressor on first stage choice such that individuals were more likely to stay with the same first stage choice after the stressor as compared with before the manipulation ($B = 0.14$, $p < 0.001$). There was also a significant reward × transition interaction ($B = 0.24$, $p < 0.001$), denoting that subjects stayed more often after common trials, when they were rewarded and stayed after rare trials when they were not rewarded. There was also a significant Transition x Pre/Post-Stressor interaction ($B = -0.048$, $p = 0.049$) as well as a Transition × Depression interaction ($B = -0.051$, $p = 0.026$). Of particular interest here, there was a significant four-way Reward x Transition x Pre/Post-Stressor x Depression severity interaction ($B = -0.047$, $p = 0.046$) indicating that the decision making of individuals with lower levels of depression were less impacted by the stressor than individuals with higher levels of depression.[3] This relationship is illustrated in Fig. 2.

Table 1
Results from logistic regression testing the association between model-based/model-free decision making individual differences in depression before vs. after the stressor. DV: Whether the participant made the same first stage choice as on the previous trial; Reward: Whether the previous trial was rewarded or not; Transition (Common vs. Uncommon): Whether the choice at the first stage previous trial led to the common (70%) or uncommon (30%) planet; stressor (pre vs. post): Whether this trial occurred prior to or following the stressor; Term: Semester number.

Coefficient	Estimate (SE)	p-value
Intercept	1.300 (0.110)	< .001***
Reward	0.515 (0.035)	< .001***
Transition (Common vs. Uncommon)	0.029 (0.026)	0.264
Stressor (pre vs. post)	0.142 (0.035)	< .001***
PHQ-9	−0.045 (0.080)	0.579
Term (Factor 1 vs. 0)	0.209 (0.175)	0.232
Term (Factor 2 vs. 0)	0.186 (0.152)	0.221
Reward x Transition	0.238 (0.034)	< .001***
Reward x Stressor	0.036 (0.025)	0.152
Transition x Stressor	−0.048 (0.024)	0.049*
Reward x PHQ-9	−0.001 (0.033)	0.976
Transition x PHQ-9	−0.051 (0.023)	0.026*
Stressor x PHQ-9	0.011 (0.033)	0.731
Reward x Transition x Stressor	−0.020 (0.027)	0.456
Reward x Transition x PHQ-9	−0.004 (0.032)	0.902
Reward x Stressor x PHQ-9	0.014 (0.022)	0.532
Transition x Stressor x PHQ-9	−0.031 (0.021)	0.143
Reward x Transition x Stressor x PHQ-9	−0.047 (0.024)	0.046*

To examine whether these effect were specifically due to changes in model-based decision making following the stressor, we re-ran these same analyses but utilized only the trials occurring prior to the manipulation. There was no Reward x Transition x PHQ-9 effect on first-choice behavior using solely the data before the stressor occurred ($B = 0.04$ $p = 0.32$). Similarly, to test whether depression severity at clinical levels may distinguish clinical vs. non-clinical depression (prior to the stressor), we binarized depression severity ($PHQ9 \geq 11$ vs. $PHQ9 < 11$) and performed the same multilevel analysis to examine model-based decision-making prior to the stressor. There was also no Reward x Transition x Depression (binarized) interaction ($p = 0.21$) indicating again that model-based decision making was not associated directly with depression prior to any manipulation. This indicates that under more neutral conditions (i.e., relatively less negative affect), the decision-making styles of individuals at higher risk for depression and those at lower risk for depression are more similar than comparing changes in model-based decision making. These data highlight the importance of research utilizing paradigms that integrate cognition and emotion.

3.5. Change in model-based decision making & trait anxiety

To examine whether these relationships were also associated with individual differences in trait anxiety, we further examined whether the effects of model-based decision making before vs. after the stressor

[3] We ran an additional analysis utilizing Valence rating but not the dichotomous condition. However, the Reward x Transition x Valence Rating x Depression Levels was not significant ($p > 0.5$).

Table 2
Results from logistic regression testing the association between model-based/model-free decision making individual differences in trait anxiety before vs. after the stressor. DV: Whether the participant made the same first stage choice as on the previous trial; Reward: Whether the previous trial was rewarded or not; Transition (Common vs. Uncommon): Whether the choice at the first stage previous trial led to the common (70%) or uncommon (30%) planet; Stressor (pre vs. post): Whether this trial occurred prior to or following the stressor; Term: Semester number.

Coefficient	Estimate (SE)	p-value
Intercept	1.307 (0.112)	< .001***
Reward	0.515 (0.035)	< .001***
Transition (Common vs. Uncommon)	0.029 (0.026)	0.271
Stressor (pre vs. post)	0.14 (0.035)	< .001***
STAI	0.05 (0.082)	0.540
Term (Factor 1 vs. 0)	0.224 (0.171)	0.189
Term (Factor 2 vs. 0)	0.139 (0.153)	0.364
Reward x Transition	0.236 (0.034)	< .001***
Reward x Stressor	0.035 (0.025)	0.168
Transition x Stressor	−0.049 (0.024)	0.044*
Reward x STAI	0.016 (0.034)	0.640
Transition x STAI	−0.024 (0.023)	0.294
Stressor x STAI	−0.032 (0.034)	0.341
Reward x Transition x Stressor	−0.021 (0.027)	0.423
Reward x Transition x STAI	−0.005 (0.032)	0.866
Reward x Stressor x STAI	0.021 (0.023)	0.360
Transition x Stressor x STAI	−0.03 (0.022)	0.159
Reward x Transition x Stressor x STAI	−0.025 (0.024)	0.298

Table 3
Results from logistic regression testing the association between model-based/model-free decision making individual differences in anhedonia (SHAPS) before vs. after the stressor. DV: Whether the participant made the same first stage choice as on the previous trial; Reward: Whether the previous trial was rewarded or not; Transition (Common vs. Uncommon): Whether the choice at the first stage previous trial led to the common (70%) or uncommon (30%) planet; Stressor (pre vs. post): Whether this trial occurred prior to or following the stressor; Term: Semester number.

Coefficient	Estimate (SE)	p-value
Intercept	1.130 (0.115)	< .001***
Reward	0.450 (0.042)	< .001***
Transition (Common vs. Uncommon)	0.029 (0.027)	0.275
Stressor (pre vs. post)	0.148 (0.038)	< .001***
SHAPS	0.051 (0.059)	0.122
Term (Factor 1 vs. 0)	0.342 (0.177)	0.054
Term (Factor 2 vs. 0)	0.222 (0.156)	0.152
Reward x Transition	0.206 (0.036)	< .001***
Reward x Stressor	0.016 (0.027)	0.549
Transition x Stressor	−0.025 (0.025)	0.325
Reward x SHAPS	0.013 (0.026)	0.609
Transition x SHAPS	−0.009 (0.016)	0.592
Stressor x SHAPS	−0.011 (0.024)	0.640
Reward x Transition x Stressor	0.013 (0.027)	0.628
Reward x Transition x SHAPS	0.0005 (0.022)	0.983
Reward x Stressor x SHAPS	0.014 (0.017)	0.395
Transition x Stressor x SHAPS	−0.031 (0.015)	0.046*
Reward x Transition x Stressor x SHAPS	−0.034 (0.017)	0.044*

were associated with trait anxiety. As with analyses examining depression severity, we conducted a mixed-effects logistic regression analysis to quantify whether there was an association between individual differences in trait anxiety and model-based decision-making before vs. after the stressor. Similar to the model examining individual differences in depression severity, there was a main effect of reward ($B = 0.51$, $p < 0.001$) on first stage choice, indicating that individuals repeated their first-stage spaceship choice more often if the previous trial was rewarded. There was also a significant effect of the stressor on first stage choice such that individuals were more likely to stay with the same first stage choice after the stressor as compared with before the stressor ($B = 0.14$, $p < 0.001$). There was also a significant reward × transition interaction ($B = 0.24$, p's < 0.001), denoting that individuals repeated the same first-stage choice more frequently if the transition was common, rather than uncommon. There was also a significant Transition x Pre/Post-Stressor interaction ($B = -0.049$, $p = 0.04$). Unlike the model with individual differences in depression, there was no Transition x trait anxiety interaction ($B = -0.024$, $p = 0.29$). But, there was no significant four-way Reward x Transition x Pre/Post-Stressor x STAI interaction ($B = -0.025$, $p = 0.256$; Table 2).

3.6. Additional analyses examining specificity

We followed-up these initial results, with tests to examine the specificity of the findings. First, we performed the same mixed-effects logistic regression analysis with depression severity as above, but included individual differences in trait anxiety as an additional additive main-effect covariate. Including individual differences in trait anxiety into the model did not account for the four-way Reward x Transition x Pre/Post-Stressor x Depression severity interaction ($B = -0.01$, $p = 0.044$). The decision making of individuals with lower levels of depression were less impacted by the manipulation than individuals with higher levels of depression above and beyond individual differences in trait anxiety. This provides some evidence that susceptibility to become less model based under states of increased stress may be more associated with individual differences in depression. We attempted to run a full model with trait-anxiety included as an interactive factor (e.g., Reward x Transition x Pre/Post-Stressor x STAI), but because of the correlation between the PHQ and STAI, the model did not converge.

Second, there is longstanding theoretical and empirical work suggesting that anhedonia perhaps most prominently differentiates risk for depression from that of anxiety (Clark & Watson, 1991). We thus, performed a second follow-up analysis to test whether individual differences in anhedonia using the SHAPS similarly predicted the magnitude of how much the stressor would impact model-based decision making. Indeed, using the SHAPS, there was a significant four-way Reward x Transition x Pre/Post-Stressor x Anhedonia interaction ($B = -0.04$, $p = 0.037$; Table 3). Similar to the analyses examining individual differences in depression severity, individuals reporting higher levels of anhedonia were more susceptible for stress to impact their decision-making.

4. Discussion

Learning to flexibly make decisions that lead to the best possible outcomes is critical for successfully navigating one's environment. It has been suggested that flexible decision-making may be impaired in individuals at-risk for mood and anxiety disorders, particularly when under stress (Huys, Daw, & Dayan, 2015a; Huys et al., 2015b). To test the hypothesis that individuals high in depression and/or anxiety would demonstrate more habitual, and less model-based decision making in the face of stress, we utilized a two-stage decision making task that distinguishes flexible and goal-directed decision making (model-based behavior) from more reflexive and automatic decision making (model-free behavior). A social stressor, which served as an experimental manipulation, was inserted at the halfway point of the task. We subsequently compared task behavior before vs. after the stressor. Results demonstrated that while there was no significant impact of the manipulation on decision making (in fact, approximately half of our sample increased in their model-based behavior after the stressor; see Fig. 1), the decision making of individuals reporting higher levels of depression was more impacted by the stressor than those reporting lower levels of depression.

A number of follow-up analyses further reveal these associations with depression. Because anhedonia has been suggested to be a factor specific to depression (whereas negative affect is thought to be shared across depression and anxiety), we tested whether individual differences in anhedonia predicted susceptibility to become more reflexive in

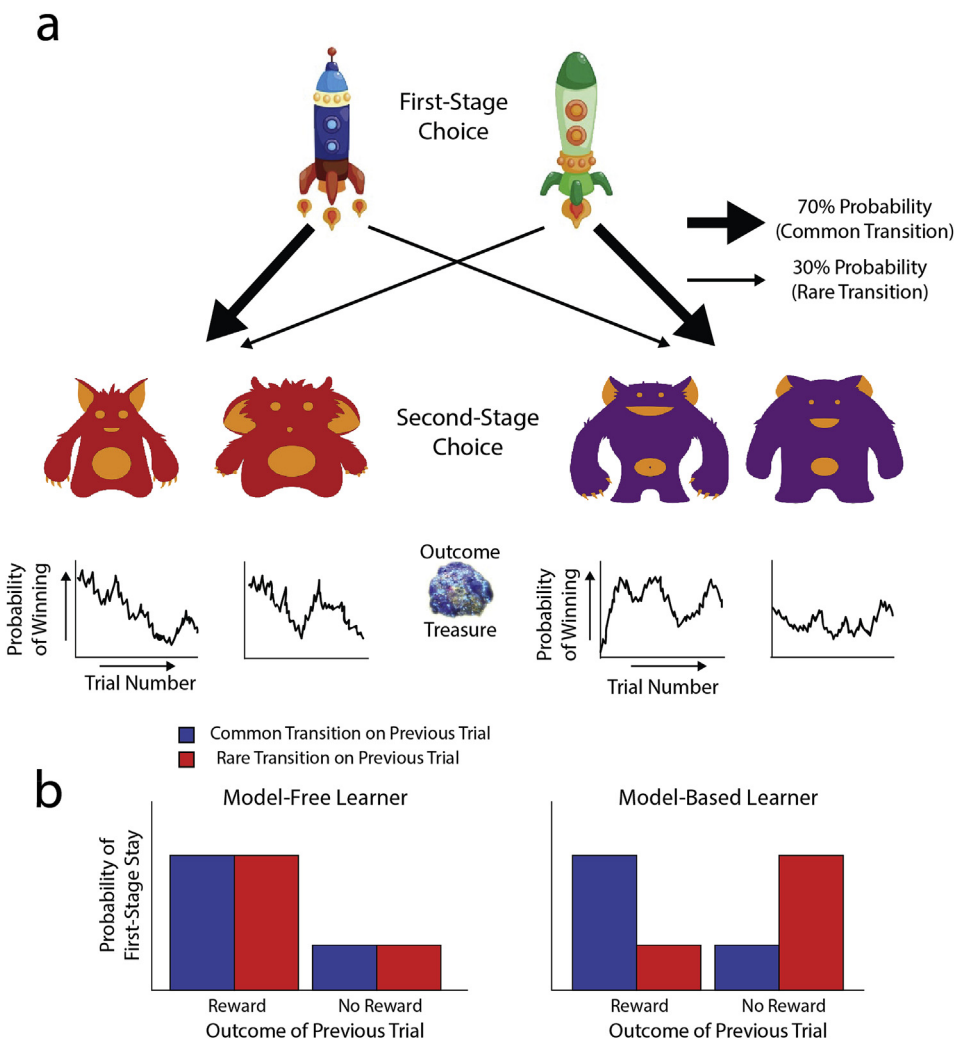

Fig. 1. Design of the sequential spaceship task (a), and idealized model-free and model-based behavior (b). On each trial, participants chose between two spaceships (first-stage choice), which was followed by a probabilistic transition to a red planet or a purple planet. Then participants chose between two aliens (second-stage choice) and were rewarded with space treasure or not. The probability of winning space treasure is presented as a function of trial for each alien. The bar graphs show, for idealized model-free and model-based learners, the probability of making the same choice on the next trial (i.e., a first-stage stay) as a function of the outcome and transition type (common or rare) of the previous trial. Taken from (Decker et al., 2016). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

decision-making following the stressor. Indeed it did; individuals reporting higher levels of anhedonia were more susceptible to the manipulation. Given the high rates of overlap between individual differences in trait anxiety and depression we were also interested in examining the specificity of the relationship between decisional style and specific aspects of mood and anxiety. Our design allowed us to take a transdiagnostic approach to examine whether the effects were due to processes shared across depression and anxiety, or whether they may be uniquely associated with particular symptoms (Brown et al., 1998; Clark & Watson, 1991). Our results tentatively indicate that the individual susceptibility to reductions in model-based behavior under stress may be more associated with processes associated with depression.

In line with our findings here, a recent report using a large non-clinical sample found that there was no significant association between individual differences in 'anxious-depression' (a *trans*-diagnostic factor compiled from various self-report measures using factor analysis) and model-based behavior under neutral conditions (Gillan et al., 2016). However, Gillian et al. did find that less model-based behavior under neutral conditions was associated with factors underlying individual differences in compulsive behavior and intrusive thought (thought to be more related to Obsessive Compulsive Disorder than trait anxiety or major depression). Insofar as depression symptoms did not predict deficits in model-based behavior in these results, we replicate Gillan et al.,'s null-result; however, we also extend it by demonstrating that under conditions of stress individuals with higher rates of self-reported depression are susceptible to become more reflexive in their decision making than those with lower rates of depression.

To date, only two additional studies have examined changes in model-based decision making as a function of acute stress. Both of these investigations revealed that individuals who experienced the greatest increases in cortisol in response to a stressor, were also those who exhibited smaller model-based contributions to choice after the stressor (Otto et al., 2013b; Radenbach et al., 2015). Furthermore, results demonstrated a larger working memory capacity had a protective effect upon an individual's model-based behavior in the face of a stressor (Otto et al., 2013b). Although neither cortisol, nor working memory capacity were acquired in the current sample we did use a well validated method to induce stress—specifically a variation of the Trier Social Stress Test—as done in the Radenbach et al. study (Radenbach et al., 2015). Based on this literature and our parallel findings, we hypothesize that a possible mechanism by which the stressor evoked a change away from model-based behavior in individuals with heightened negative affectivity, possibly by occupying individuals' cognitive processing resources, leaving few resources 'left' to perform demanding model-based computations during choice (Otto, Gershman, Markman, & Daw, 2013a; Otto, Skatova, Madlon-Kay, & Daw, 2015).

There is a large body of research demonstrating executive function deficits in individuals with heightened susceptibility to mood and anxiety disorders (Snyder, 2013). However, recent meta-analyses suggest that in a neutral, executive function deficits are non-specific (Snyder, Miyake, & Hankin, 2015). That is, most disorders show similar deficits on the same executive function tasks. As a result, it has been suggested that in order to uncover disorder specific mechanisms, stress should be

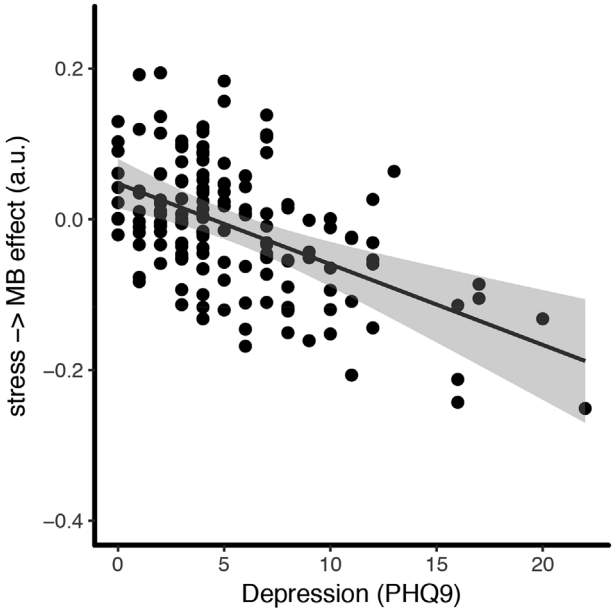

Fig. 2. Change in model-based behavior from before to after the stressor. Values on the y-axis are the individual model-based effect sizes calculated from the mixed-effects logistic regression, conditioned on the estimated population-level effects. These effects represent the estimated model-based behavior after the stressor minus before the stressor. Results indicate that decision making of individuals reporting higher levels of depression was more impacted by the stressor than those reporting lower levels of depression.

induced to examine individual differences in executive function (Robinson, Watkins, & Harmon-Jones, 2013). Tapping these interactions between emotion and cognition may represent one primary pathway to better deconstruct cognitive and affective processes involved in internalizing disorders.

The current study should be interpreted in light of several limitations. First, that we did not perform a structured interview to assess whether anyone in the sample in fact suffered from a depression or anxiety disorder somewhat limits our ability to generalize the effects to psychiatric disorders writ large. Despite the fact that categorical cut-points are often arbitrary distinctions on continuous distributions (Altman & Royston, 2006), the sample likely has a somewhat restricted range. Because we might not have been sampling from the full range of possible severity for anxiety and depression symptoms, our power may have been limited to estimate the true effect size. Second, and as discussed above, previous work has utilized salivary cortisol to measure response to the stressor, and the magnitude of the cortisol response has been associated with the stress-evoked decrement in model-based behavior (Otto et al., 2013b). It may be that cortisol reactivity further mediates the relationship between stress-induced reductions in model-based choice behavior and risk for mood disorders. We intend for future work to collect saliva samples to address this questions. Relatedly, from these data, it is unclear whether the stressor achieved its effects on model-based decision making via impacting arousal generally or more specifically via an increase in negative affect (Guitart-Masip, Duzel, Dolan, & Dayan, 2014). Third, these data can only speak to negative affect associated with trait anxiety and mood symptoms. Our investigation did not consider other types of anxiety or related syndromes, which are linked with negative affect and may be associated with deficits in model-based learning. For example, both impulsive traits and obsessive-compulsive symptoms have been connected with lower levels of reliance upon model-based decision strategies (Deserno et al., 2015; Gillan et al., 2016). Therefore, future work should examine the role of stress in modulating the relationship between various psychiatric symptoms and model-based decision-making. Fourth, a potential criticism might be the lack of a control condition without a stressor. Having such a control condition could enhance confidence that any effects would not be due to the time one task, boredom or motivation. However, there was neither a Reward x depression severity interaction ($p = 0.98$), nor a significant Reward x Stressor x depression severity interaction ($p = 0.532$). This indicates that motivation or reactivity to reward did not decrease across the task differentially for individuals at greater risk for depression. Nonetheless, future work should include an additional task to control for individual differences in cognitive capacity or directly measure current cognitive load. Lastly, research should attempt to distinguish the processes involved in the effect of trait negative affect on susceptibility to become more reflexive in decision making after stress or stressors that engender negative affect. Whether these effects are due more to physical or cognitive features of anxiety and/or whether they may be associated with rumination can further delineate the cognitive processes that underlie why one becomes less reliant upon model-based choice after stress. Related inquiry into the neural underpinnings of these associations could expand on our existing understanding of which specific neurotransmitter systems may play a pivotal role in model-based behavior (Doll, Bath, Daw, & Frank, 2016; Worbe et al., 2016).

While tentative and requiring replication, these results add to the growing literature that changes in decision making of individuals at risk for mood disorders are predominantly apparent under conditions of stress. These results suggest that behavioral therapists treating patients at risk for mood disorders may want to monitor the decision making of their patients particularly when those individuals are experiencing stressful situations that may heighten negative affect. These data suggest that it is during stress, individuals at highest risk may be more likely to use reflexive and habitual cognitive processes to make decisions.

The ability to continue to make goal-directed choices and engage in flexible decision-making is essential for adaptively navigating one's environment and successful self-regulation in the face of stress and increases in negative affect. This study demonstrated that individuals with higher levels of depression were susceptible to become more reflexive in their decision making after a stressor than individuals reporting lower levels of depression. These findings demonstrate that a stressor may be required to uncover impairments in flexible decision making among individuals at risk for depression.

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Individuals interested in the analysis R-code are encouraged to email the corresponding author, aheller@miami.edu.

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