Borderline Personality Disorder and Learning: The Influences of Emotional State and Social versus Nonsocial Feedback

BORDERLINE PERSONALITY DISORDER AND LEARNING: THE INFLUENCES OF EMOTIONAL STATE AND SOCIAL VERSUS NONSOCIAL FEEDBACK

A Thesis Presented

by

ELINOR E. WAITE

Submitted to the Graduate School of the
University of Massachusetts Amherst in partial fulfillment
of the requirements for the degree of

MASTER OF SCIENCE

September 2022

Department of Psychological and Brain Sciences

Division of Clinical Psychology

BORDERLINE PERSONALITY DISORDER AND LEARNING: THE INFLUENCES OF EMOTIONAL STATE AND SOCIAL VERSUS NONSOCIAL FEEDBACK

A Thesis Presented

by

ELINOR E. WAITE

Approved as to style and content by:

DocuSigned by:
Katherine Dixon-Gordon
FE36A90A5DB1462...
Katherine L. Dixon-Gordon, Chair

DocuSigned by:
Andrew Cohen
26E4DD6D38EC450...
Andrew L. Cohen, Member

DocuSigned by:
Jennifer McDermott
8088012F6929423...
Jennifer M. McDermott, Member

DocuSigned by:
Farshid Hajir
9FAA8567A0B744A...
Farshid Hajir, Acting Department Chair
Department of Psychological and Brain Sciences

ABSTRACT

BORDERLINE PERSONALITY DISORDER AND LEARNING: THE INFLUENCES OF EMOTIONAL STATE AND SOCIAL VERSUS NONSOCIAL FEEDBACK

SEPTEMBER 2022

ELINOR E. WAITE, B.A., UNIVERSITY OF NEVADA RENO

M.S., UNIVERSITY OF MASSACHUSETTS AMHERST

Directed by: Professor Katherine Dixon-Gordon

Borderline personality disorder (BPD) has been linked to impulsive behaviors, interpersonal difficulties, and emotional reactivity. Although these impairments imply underlying deficits in decision-making, theory suggests that such deficits may be context dependent. Both emotional state and social context may influence learning in BPD. Reinforcement learning models offer an avenue to parse types of impairments in learning. The current study used reinforcement learning models to examine whether the type of feedback (social vs. nonsocial) moderates the association between BPD and learning under conditions of distress. Adults with BPD (*N* = 37), subthreshold BPD (*N* = 29), and without BPD (*N* = 65) completed a diagnostic interview and a computerized learning task after both neutral and negative emotion inductions. We examined learning outcomes, including accuracy, learning rate, and stochasticity. We used multilevel models to examine the associations between BPD criteria, feedback type, and emotional state on several different learning outcomes. We found that elevated BPD features were associated with greater negative emotion-related increases in the loss learning rate in the training phase and increases in the gain learning rate in the test phase. Further, social feedback was associated with more normalized learning rates for participants with BPD. We discuss possible interpretations of our learning rates, as research is mixed on the implications of higher and lower learning rates. Understanding the decision-making and learning deficits associated with BPD will further explain the impulsive and reckless behaviors associated with the disorder, as well as inform new methods to teach effective skills during treatment.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Borderline personality disorder (BPD) is a serious psychiatric condition characterized by instability in affect, identity, relationships, and marked self-destructive impulsive and risky behaviors (see Appendix A for full diagnostic criteria; American Psychiatric Association, 2013). The community population prevalence of BPD is reported to be between 1.6% and 5.9% (APA, 2013); however, the prevalence is approximately 6% in primary care settings, 10% in outpatient mental health settings, 20% among psychiatric inpatients (APA, 2013), and 10% among college students (Meaney et al., 2016). Further, nearly 18% of all deaths by suicide are attributable to BPD (Bolton & Robinson, 2010). This disorder is therefore associated with high rates of mortality due to suicide and results in a high societal and economic toll (Gunderson et al., 2018; van Asselt et al., 2007). Thus, efforts to better understand and ameliorate the symptoms associated with BPD are a critical public health priority.

Many of the problems associated with BPD may be due, in part, to the disadvantageous decision-making associated with this condition (Paret et al., 2017; Schuermann et al., 2011; Svaldi et al., 2012). Pinpointing specific deficits in the decision-making process seen in BPD may offer the possibility of explaining why people with BPD engage in risky behaviors, such as reckless driving, gambling, substance use, disordered eating, risky sexual behavior, and non-suicidal self-injury (Coffey, Schumacher, Baschnagel, Hawk, & Holloman, 2011; Hamza, Willoughby, & Heffer, 2015; Tull, Gratz, & Weiss, 2011). Such decision-making may differ based on emotional state (Dixon-Gordon et al., 2018) or in social versus nonsocial situations among BPD populations (Fineberg et al., 2018; Hackel et al., 2015). The present study will use a novel approach to fill an important gap in the literature, leading to a stronger understanding of the underlying learning deficits for people with BPD, as well as provide significant clinical implications for teaching effective skills.

1.1 BPD and General Decision-Making Problems

Decision-making deficits among people with BPD are well-documented, although further research is needed to examine what factors may drive this impairment. Recent research shows disadvantageous decision-making is common among BPD populations relative to controls, particularly on delay discounting tasks, such that people with BPD typically opt for rewards received in the short term, as opposed to waiting longer to receive a larger reward (Barker et al., 2015; see for review Paret et al., 2017). Further, this preference for immediate rewards over larger rewards in the future has been shown to be pervasive problem for people with BPD, and not solely present during times of distress (Lawrence et al., 2010). People with BPD are also shown to make more risky decisions than healthy controls (Svaldi et al., 2012), particularly when the decision is framed as a potential loss (Sánchez-Navarro et al., 2014). In general, people with BPD are less avoidant of risk when compared to healthy controls (Endrass et al., 2016). Whereas healthy individuals tend to choose low-risk options (with a small gain or loss) significantly more often than high-risk options (with a large gain or loss), participants with BPD do not show a preference for either option, perhaps suggesting that the outcome of their choice does not have much bearing on future choices.

Several studies have explored decision-making processes in BPD using the Iowa Gambling Task (IGT), a gambling task in which consequences occur immediately after every choice. Generally, participants with BPD make fewer advantageous decisions (Haaland & Landrø, 2007) and more disadvantageous decisions (LeGris et al., 2014) than healthy controls. Indeed, whereas performance on the IGT predicted BPD diagnostic status, no other executive functioning tasks (e.g., working memory, inhibitory control) were associated with BPD (LeGris et al., 2014). In an effort to explore how feedback on earlier trials of the IGT predicted later task performance in BPD, research has focused on performance on the five trial blocks of the IGT (20 trials per block; Maurex et al., 2009). On the first two trial blocks, the BPD and healthy control groups did not differ in their number of disadvantageous decisions. Yet additional analyses of the last three trial blocks, showed that the control group learned from past feedback significantly better than the BPD group, as the control group showed significantly more improvement in task performance than the BPD group. This persistent disadvantageous decision making suggests that those individuals with BPD did not learn as much from the loss feedback or were not paying attention to the feedback, resulting in a less risk averse profile on later blocks relative to healthy counterparts.

Many of these decision-making problems may be driven by difficulties in using feedback to guide decision making. For instance, the findings of studies of riskier decisions when choices were framed in terms of loss (e.g., Sanchéz-Navarro et al., 2014) suggest that individuals with BPD may have less aversion to losses or punishment, which in turn may mean that such feedback is less useful in guiding their decision making. Indeed, one study of prisoners suggested that those with BPD were more likely to risk a larger loss when the chance of a reward was high; while prisoners without BPD were less likely to take this risk (Kirkpatrick et al., 2007), suggesting that people with BPD might weigh the possibility of reward more highly, even when confronted with a large consequence. Further, despite receiving consistent feedback on the consequences of their decisions on a task with unambiguous risk, people with BPD continued to choose the riskier and less optimal option, suggesting that they had less capacity to use the feedback to their advantage, as compared with a control group (Svaldi et al., 2012). Taken together, people with BPD may overweight potential rewards, even when the risk or size of punishment is high.

In sum, people with BPD exhibit difficulties making advantageous decisions despite feedback. This deficit may be driven by a tendency to seek reward rather than avoid punishment. Importantly, this deficit is unlikely to be due to hasty, careless decision making, given that individuals with BPD have actually been shown to take longer to make decisions than their non-clinical counterparts (Bazanis et al., 2002). Thus, deficits in the ability to integrate feedback to inform future decisions may be a key element leading to poor decision-making in BPD.

1.2 Reinforcement Learning

Reinforcement-learning models are one approach to understand decision-making deficits. Reinforcement learning refers to the ability to learn from feedback and modify future decisions based on seeking rewards or avoiding punishments. Individuals must explore and exploit their environment to maximize reward, minimize loss, and learn more about the world around them to make more effective behavioral decisions in the future

(Sutton & Barto, 2018). During the exploration process, individuals learn more about the world around them, as well as what behaviors, or actions, elicit rewards, and which elicit punishments. What they have learned allows them to minimize loss and maximize gain in the exploitation stage, by making decisions more likely to lead to rewards and decrease the risk of punishment. When the outcomes of an action surpass the expectations, stimulus-action associations are strengthened and individuals are more likely to engage in the reinforced action in the future (Hebb, 1949), whereas associations are weakened when outcomes fall short of expectations (Holroyd & Coles, 2002). Thus, reinforcement-learning models capture how trial-by-trial feedback based on past actions affects current decisions and can be used to parse specific deficits in the decision-making process. Reinforcement-learning models help us to understand the probability of an action yielding a reward as a function of the expected and actual outcomes, and generate relevant learning parameters, such as the degree to which recent feedback alters the next decision (i.e., learning rate) and the degree to which responses are more rigid or random (i.e., stochasticity; Maia & Frank, 2011). Of note, although lay understanding of learning rates often assumes higher learning rates are better, such learning rates may lead to settling on a suboptimal action earlier in the exploration process. Whereas some researchers have proposed that lower learning rates may be optimal to allow slow integration of information (e.g., Cavanagh et al., 2011), other research suggests that higher learning rates are associated with fewer errors (Dombrovski et al., 2010). Such models therefore shed light on specific alterations in the processes underlying decisions-making errors.

Although research on reinforcement learning models in BPD populations remains scarce, impairments in reinforcement learning have been linked to broad domains of behavioral, emotional, and cognitive difficulties. Namely, researchers have drawn connections between difficulty learning from feedback and disadvantageous decision-making, working memory impairments, externalizing behaviors, impulsivity, and interpersonal difficulties in a variety of sample populations (Endres et al., 2012; Fineberg et al., 2014; Paret et al., 2017; Segers et al., 2018). In addition, deficits in reinforcement-learning abilities have been linked neurologically and behaviorally to specific psychopathological disorders. For instance, an impaired ability to adjust learning to volatility, or unexpected consequences, has been linked to both anxiety and depression (Gagne et al., 2020). Researchers have also seen lower valuation of, and sensitivity to, rewards in depressed individuals than their control counterparts (Chen et al., 2015; Huys et al., 2013; Pizzagalli et al., 2009; Rock et al., 2013). However, despite this lower valuation of rewards or punishment, individuals with depression and anhedonia have been shown to have relatively intact learning rates (Chase et al., 2010; Huys et al., 2013; Kunisato et al., 2012). In terms of the relative stochastic versus deterministic approaches to learning, research is mixed. Research with depression and gambling disorder has shown no differences in random exploration between those with and without psychopathology (Rothkirch et al., 2017; Wiehler et al., 2021)., while research with anxiety shows more deterministic responding in the symptomatic group (Aylward et al., 2019). Reinforcement learning deficits have also been shown among individuals with attention deficit-hyperactivity disorder, schizophrenia, substance abuse disorders, and

BPD (Maia & Frank, 2011), suggesting that this may be a transdiagnostic deficit present in a variety of psychopathology.

Of note, populations characterized by clinical problems that overlap with BPD also evidence altered learning. For instance, individuals with suicide attempt histories have less anticipation of and alterations in processing reward, relative to individuals without suicide attempt histories (Tsypes et al., 2020). However, reinforcement learning research with BPD populations is still in its infancy (Fineberg et al., 2019). Preliminary data suggest that learning accuracy is lower in individuals with (vs. without) BPD (Fineberg et al., 2019), but such studies often have not evaluated factors likely to influence learning in this population.

1.2.1 Influence of Emotions on Learning in BPD

There is some emerging work suggesting that emotions may influence learning in BPD. Even in non-BPD samples, exposure to stressors in the laboratory influences learning (Cavanagh et al., 2011). Negative emotional reactivity led to greater punishment-learning accuracy among punishment-sensitive participants, and the reverse was true among punishment-insensitive participants. Similarly, instructed negative rumination led participants with depression to be less sensitive to punishment than to reward, whereas distraction resulted in comparable sensitivity to punishment and reward (Whitmer et al., 2012). Moreover, individuals with high levels of BPD features show more impulsive behaviors on an avoidance learning task after a negative emotion induction (Chapman et al., 2008, 2010). Only recently have few researchers begun to use reinforcement learning models to explore decision-making and emotions among BPD samples specifically. One recent study used a forced-choice probabilistic task to assess whether neutral or negative emotional state impacted participants' ability to learn from feedback (Dixon-Gordon et al., 2018). In particular, relative to healthy controls, individuals with BPD showed poorer high-conflict punishment learning accuracy following a negative emotion induction, controlling for learning after a neutral emotion induction. Yet this study revealed no group differences in learning rates or stochasticity. Other research likewise points to the influence of emotional arousal on reinforcement learning in BPD. In particular, stimulus arousal, induced through the use of aversive scenes in the learning task, predicted errors in acquisition learning, suggesting that difficulties with learning may relate to the emotional state for participants with BPD (Paret et al., 2016). Thus, negative emotional states appear to heighten deficits in reinforcement learning among BPD samples, suggesting the importance of examining learning across conditions. Yet research in this area remains scant, and further work is needed to replicate these findings.

1.2.2 Influence of Social Cues on Learning in BPD

Learning in social contexts may differ from learning in nonsocial contexts, particularly for individuals with BPD. Social feedback, or rewards and punishments from the people we interact with, is one of the primary forms of feedback humans receive in the world. Yet, several aspects of learning from social situations differ from other forms of learning (Hackel et al., 2015). Similar to general reinforcement learning models, in which people must be able to explore and exploit their environment in order to achieve the desired outcome, people must be able to explore and exploit the social environment in order to minimize loss and maximize reward. However, exploration in social contexts not only involves learning about the typical outcome from one's behaviors but also includes the need to learn about the people with whom one interacts. A given behavior will not always elicit the same reward, as in general reinforcement learning; in social reinforcement learning, this reward will be modified by the other people involved. What is learned from these experiences will influence decisions made in future interpersonal encounters in order to achieve the desired outcomes.

Although research into the influence of social situations on decision making in BPD is sparse, exploring such contexts is especially important to consider in BPD populations as instability in interpersonal relationships is a core feature of the disorder. A recent study showed that people with BPD, when compared with healthy controls, weigh social cues stronger than nonsocial cues, yet still show a decreased ability to learn from social cues, particularly when the likelihood of receiving a reward was variable (Fineberg et al., 2018). Of note, in this study, whereas healthy individuals had faster learning rates when information became more volatile, those with BPD did not show the same increase in learning rates, suggesting inefficient updating when conditions required it.

Therefore, participants with BPD may over rely on social cues. Yet, these individuals may be particularly likely to misinterpret this social feedback. Indeed, individuals with BPD misinterpret neutral situations, feel socially rejected during normal inclusion situations, and have difficulty cooperating after experiencing or perceiving social disappointment (Lis & Bohus, 2013). Similarly, another study showed that people with BPD rated fair offers during a social teamwork game as less fair than healthy controls (De Panfilis et al., 2019). People with BPD also rejected a larger number of fair offers than healthy controls. Taken together, participants with BPD may be biased to underestimating positive input or feedback from others during social interactions.

BPD has been linked to alterations in the perception of facial cues of emotion, which could indicate social reward or punishment. Individuals with BPD identified the displayed facial affect at a lower intensity across emotions, but mostly in terms of identifying happiness and anger (Lynch et al., 2006). Yet individuals with BPD seem to have biases in interpreting emotions relative to non-BPD peers, showing a tendency to over-attribute disgust (Unoka et al., 2011) and be more sensitive to anger, but under-attribute sadness and fear and identify happiness more slowly (Ferreira et al., 2018). In addition, those with BPD show a generally negative bias to interpreting neutral expressions (Dyck et al., 2008). Thus, individuals with BPD may more readily perceive punishing social feedback like anger, but less readily perceive rewarding social feedback like happiness. In other words, when feedback is provided in the form of facial expressions and cues, as it often is, people with BPD may be misinterpreting and overweighting this feedback, leading to altered learning.

1.3 The Current Study

Extending existing research, we aimed to examine the influence of emotions and type of feedback (social versus nonsocial) on the relationship between BPD symptoms and learning performance. Learning was assessed in terms of accuracy, modeled learning rates, and the tendency towards stochastic vs. rigid responding. Participants completed were randomized to receive either nonsocial or social feedback during a forced choice probabilistic learning task, which they completed twice, following both a neutral mood induction and negative mood induction. We hypothesized that (1) BPD symptoms would predict (a) poorer learning accuracy (especially on more difficult trials) and (b) potentially lower learning rates, as some research suggests lower learning rates result in more errors. Further, this association may be evident only in negative (vs. neutral) emotion conditions. There were less data to guide us in understanding the influence of social feedback on learning. The increased weighting of social cues may enhance learning from such cues in BPD, whereas the potential to misinterpret these cues may impair such learning. Nevertheless, we hypothesized that (2) BPD symptoms would interact with social conditions in predicting (a) poorer learning accuracy (especially on more difficult trials) and (b) potentially lower learning rates, with worse outcomes in social (vs. non-social) conditions. We also explored the influence of BPD, emotional state, and social context on stochastic vs. rigid learning, although we did not have an a priori hypothesis.

CHAPTER 2

METHODS

2.1 Participants

As part of a larger study, participants (N = 131) with a range of BPD symptoms were recruited from the University of Massachusetts Amherst campus and the surrounding community. See Table 1 for demographic characteristics of our sample. Participants from the community were recruited via flyers in the community and online. To be included in our study, participants had to be 18 to 55 years of age (to address age-related deficits in learning; Rönnlund, Nyberg, Bäckman, & Nilsson, 2005), able to read and complete online questionnaires, and fluent English speakers. In order to ensure an adequate range of BPD symptoms, participants were screened (via online university prescreen or by phone) for BPD features on the Personality Assessment Inventory – Borderline Features Scale (PAI-BOR; Morey, 1991), and the Structured Clinical Interview for Personality Disorders – BPD portion (SCID-PD) screening questionnaire (First, Williams, Karg, & Spitzer, 2015). Participants were randomly assigned to receive either social or nonsocial feedback on the learning task.

2.2 Procedures

All procedures in the present study were approved by the institutional review board, and all participants provided written informed consent. Participants were provided financial compensation or course credit (for student participants). After the initial screening and informed consent, participants completed the study during two in-person sessions. During the first session, participants completed the Mini International

Neuropsychiatric Interview (MINI 7.0.2; Sheehan et al., 1998) and the Structured Clinical Interview for Personality Disorders – BPD portion (SCID-PD; First et al., 2015). All diagnostic interviews were administered by trained lab personnel, who received supervision during the course of the study. Participants were asked to describe a recent upsetting social situation; this narrative was used to generate a stressful mood induction script that will be recorded and played back to participants to induce stress at a later point of the study, consistent with prior protocols (Gratz et al., 2011). Participants then completed online baseline questionnaires, including demographics. These questionnaires were sometimes completed during a later in-person session on a case-by-case basis, in order to reduce participant burnout. To manage risk during this, and all, sessions, participants were administered a risk assessment (University of Washington Risk Assessment Protocol, UWRAP, Reynolds, Lindenboim, Comtois, Murray, & Linehan, 2006)) at the beginning and end of every session.

During the second in-person session, participants completed a forced choice probabilistic learning task (Cavanagh et al., 2011; Frank et al., 2005). Self-report baseline emotional state was measured with the Positive and Negative Affect Schedule (PANAS; Watson, Clark, & Tellegen, 1988). Participants were then administered a neutral mood induction, during which they were asked to count the number of different colors that were displayed on a computer screen for five minutes (a "vanilla" baseline; Jennings et al., 1992), as in prior studies (Dixon-Gordon et al., 2011), then they completed the PANAS, for a second time, and the forced choice probabilistic learning task. The learning task consists of a training phase, during which participants are randomized to see either social or nonsocial feedback, and a test phase, wherein no feedback is given. Following task completion, participants listened to the stressful mood induction, a 60-second recording of the interpersonal conflict script generated from the first session, followed by a third administration of the PANAS as a confirmatory measure of emotional response to the stressful mood induction. Participants completed the learning task again, with novel stimuli and the same feedback condition as in the first administration of the task. A fixed order of the mood inductions (i.e., neutral then negative) was used to reduce potential carry-over effects of the negative mood induction if it were administered prior to the neutral mood induction.

2.3 Measures

2.3.1 Diagnostic Measures

Interviewers administered clinical interviews to characterize the sample in the initial session. The Miniature International Neuropsychiatric Interview (MINI 7.0.2) assessed mood, anxiety, substance use, and trauma-related disorders (Sheehan et al., 1998). The BPD questions from the Structured Clinical Interview for Personality Disorders (SCID-PD) assessed for the presence of a BPD diagnosis and number of BPD criteria (First et al., 2015). Trained interviewers were graduate or postbaccalaureate students supervised by a licensed psychologist; all interviews were reviewed by at least two students and the supervisor. A random subset (5.1%) of the interviews were scored for reliability purposes by the interviewers and the supervisor. Interrater reliability of BPD diagnoses for this subset of interviews was adequate (ICC (2,1) = .966).

2.3.2 **Risk Assessment Protocol**

The University of Washington Risk Assessment Protocol (UWRAP) was administered at the beginning and end of each in-person session to assess a participants' risk of self-harm at different points in the study, and to allow lab personnel the notice and opportunity to provide risk management as needed (Reynolds et al., 2006). The UWRAP assesses each participant's emotional state and urges of self-injury, substance use, and aggression towards others with a scale ranging from 1 (no distress) to 7 (high distress). If a participant reports urges for self-injury ≥ 4 at any point or an increase in distress of ≥ 2 points during the session, they will be guided through a mood improvement protocol involving skills from an empirically supported treatment, Dialectical Behavior Therapy (Linehan, 1993). This procedure has been shown to effectively reduce distress (Chapman et al., 2009; Dixon-Gordon et al., 2011; Gratz et al., 2015). A trained clinician was available to meet with a participant if necessary (in cases of continued distress). The data collected from this measure was not included in analyses.

2.3.3 Self-Reported BPD Features

The Personality Assessment Inventory – Borderline Features Scale (PAI-BOR; Morey, 1991) was used as a screening measure (see Appendix B). The PAI-BOR, a 24-item self-report questionnaire that assesses four domains of BPD features (affective instability, identity problems, negative relationships, and self-harm), was administered via an online survey or over the phone to interested participants. To complete this measure, participants decide how accurate various statements are about themselves on a scale of 0 (false) to 3 (very true). Analysis of this scale yields both overall scores and subscale scores for each of the four domains. Higher total scores on this measure indicate higher levels of BPD features, with a score of 38 serving as a clinical cutoff and indicating a likely diagnosis of BPD (Trull, 1995). Participants scoring above this cutoff were specifically invited to participate in the study, in order to obtain a broad range of BPD symptoms, although participation will be open to participants scoring below this cutoff until an adequate control condition is recruited. Internal consistency in our sample was acceptable (α = .868).

2.3.4 Self-Reported Emotional State During the Laboratory Session

The PANAS (Watson et al., 1988) was administered to assess emotional state at the beginning of the second session and after both the neutral and stressful mood inductions, as a manipulation check. The PANAS consists of 20 negative and positive affective adjectives and asks participants to rate each adjective on a 5-point Likert scale, based on to what extent they are currently feeling each emotion, in the present moment. This measure is shown to have good reliability and validity and is relatively brief; consequently, it is likely not to interfere with the effects of the mood induction. Internal consistency in our sample was acceptable at both the neutral (α = .816) and the negative induction (α = .844).

2.3.5 Probabilistic Learning Task

The learning task involves a forced choice training phase followed by a subsequent test phase (Cavanagh et al., 2011; Frank et al., 2005). During the training phase, participants were presented with stimulus pairs (i.e., AB, CD, and EF) and had to choose one of the stimuli in each pair, then were given feedback on their response. The stimuli, all of which were Japanese characters, were associated with a stochastic chance of receiving ‘Correct’ or ‘Incorrect’ feedback, such that the probability of reward for A was 80%, B was 20% (and CD and EF were 70/30% and 60/40%, respectively). During the training phase, participants learned to choose the optimal stimulus, or the stimulus more likely to be correct in each pair. Then, during the test phase, participants were presented with all possible stimulus pairs (e.g., AD, BE, CF), with no feedback provided after their responses. See Figure 1 for a depiction of the learning task. The training phase allows for an examination of participants adjustments to changing contingencies, learning acquisition, and working memory, and may be associated with the prefrontal cortex. However, the test phase captures long-term, habitual learning, and may be associated with the basal ganglia (Frank et al., 2007). Thus, we examined modeled learning parameters from both phases of the task, consistent with some prior work with this task (Cavanagh et al., 2011; Frank et al., 2007).

Participants were randomized to be in either the nonsocial or social conditions. In the nonsocial condition, participants received written feedback during the training phase (the words “correct” or “incorrect”) as in past use of this task. In the social condition, facial images from the NimStim Set of Facial Expressions stimuli set (Tottenham et al., 2009) displaying happy (reward) and anger (punishment) emotional expressions were used in place of the written words to provide feedback. The social stimuli presented to participants were matched to their gender and racial identity. This task was administered twice, with the same feedback condition each time and different stimuli, once after a neutral mood induction and again after a negative mood induction, as in previous research (Cavanagh et al., 2011; Dixon-Gordon et al., 2018). Participants were told to respond as quickly and as accurately as possible. See Figure 2 for example images of the social feedback stimuli.

In order to examine learning accuracy, we defined overall gain learning accuracy as the accuracy of choosing the most rewarding stimulus (i.e., A) over less rewarding stimuli (i.e., C, D, E, and F) during the test phase and overall loss learning accuracy as the accuracy avoiding the most punishing stimulus (i.e., B) over less punishing stimuli (i.e., C, D, E, and F). Consistent with past work, high conflict gain or loss accuracy was defined as the accuracy on trials where the chance of reward of punishment was more ambiguous. Specifically, high conflict gain learning trails were trials where the most rewarding stimulus (i.e., A) was paired with stimuli that had a greater than 50% chance of also providing a reward (i.e., C and E). Similarly, high conflict loss learning trails were trials where the most punishing stimulus (i.e., B) was paired with stimuli that had a greater than 50% chance of also providing a punishment (i.e., D and F).

CHAPTER 3

DATA ANALYTIC PLAN

3.1. Power Analysis

We conducted an a priori power analysis to determine how many participants would be required to detect a medium-sized effect of a three-way interaction between BPD, feedback, and emotion on learning outcomes using a repeated measures ANOVA. Using G*Power3 (Faul et al., 2007), we determined that approximately 131 participants are needed to detect a power of .80 and an alpha of .05.

3.2 Preliminary Analyses

We examined descriptive statistics and graphical depictions of our primary study variables (learning outcomes, BPD) variables for normality and their association to determine if these variables exhibit linear associations or some other pattern of association. Variables were transformed as necessary. In addition, we examined associations between demographic features (i.e., sex, race, age) and primary study variables (i.e., learning outcomes, BPD criteria), and variables associated with outcomes at all timepoints (given the repeated measures within individuals) but not BPD were included as covariates (Miller & Chapman, 2001). Self-report data of emotional state after the emotion inductions, will be analyzed to evaluate the efficacy of the neutral and stressful mood inductions.

In order to analyze the learning task, we excluded participants who did not select the most rewarding stimuli over the most punishing stimulus more than 50% of the time in the training phase of the neutral condition, consistent with prior research (Cavanagh et al., 2011; Frank et al., 2005).

3.3 Reinforcement Learning Computational Models

To derive learning parameters including learning rate from gain (α_G), learning rate from loss (α_L), and deterministic tendency (β), we fit participant's performance on the learning task to a reinforcement learning computational model used in prior literature (Q-learning model; Cavanagh et al., 2011; Dixon-Gordon et al., 2018; Frank et al., 2005). We fit two Q-learning models, looking both at participants' performance on the training phase and their generalization performance during the test phase. Further, our models incorporated learning rate parameters for both loss and gain (negative and positive feedback, respectively).

We generated the learning parameters using the following equation, which computes the expected value of selecting a stimulus *i* (where *i* can be stimulus A, B, C, D, E, or F):

$$Q_i(t+1) = Q_i(t) + \alpha_G[\delta_i]_+ + \alpha_L[\delta_i]_- \, , \qquad \textbf{[1]}$$

where t is the trial number and all Q_i are initialized to 0. The difference between the actual reward for each trial (R_t; 0 = incorrect or 1 = correct) and the expected reward ($Q_i(t)$; ranging from 0 to 1) will be calculated ($\delta_i = R_t – Q_i(t)$) and multiplied by learning rates from reward (α_G) and punishment (α_L) to determine stimulus value estimates for each trial [$Q_i(t)$]. The best fitting learning rates from gain (α_G) and loss (α_L) to each participants' series of choices allows us to interpret the degree to which reward or punishment impacts the following Q values. A large learning rate value (closer to 1, for both α_G and α_L) may indicate a recency effect, in which the gain or loss on a specific trial greatly impacts an individual's choice on the subsequent trial; thus, effects of feedback from an individual trial are lost over time. Likewise, a small learning rate value (closer to 0) indicates that learning is aggregated over time, as the learning rate is only updated a small amount after each trial (Frank et al., 2007).

3.4 Training Phase Models

Further, we computed the probability for choosing one stimulus over another (e.g., i over j) during the training phase:

$$P_i(t) = \frac{e^{\frac{Q_i(t)}{\beta}}}{e^{\frac{Q_i(t)}{\beta}} + e^{\frac{Q_j(t)}{\beta}}}, \qquad \textbf{[2]}$$

where β is an inverse gain parameter, representing the participant's tendency to choose the stimulus with the highest Q value or randomly choose a stimulus (exploit vs. explore, respectively). This probability will be calculated for all training trial pairings (A over B, C over D, & E over F). As the exploration parameter β increases, choices because more stochastic, i.e., differences in Q values mean less. As β decreases, choices become more deterministic.

Following this, we used a log likelihood estimate (LLE) fit of the model to each participants' responses during the training phase:

$$LLE = \log\left(\prod_t P_{i*,t}\right), \qquad \textbf{[3]}$$

where t is trial number and $i*,t$ is the choice on that trial. The best fit parameters are associated with the maximum LLE value and are predictive for a participant's series of responses during the training phase.

3.5 Test Phase Models

In order to examine generalization of learning, we used the previously generated training phase parameters, as we expected differences between learning with feedback and the generalization to trials without feedback. Q' was used to denote values for each stimulus during the test phase; further, the Q' equation will be equivalent to equation 1. However, rather than calculating probability of a choice for the training pairings, we computed the probability that a participant chooses stimulus A over each of the other stimuli (i.e., B, C, D, E, and F), based on the novel pairings seen. For example, in a situation where a participant chooses A when presented with a test pair AC:

$$P_i^{test} = \frac{e^{\frac{Q'_i final}{\beta'}}}{e^{\frac{Q'_i final}{\beta'}} + e^{\frac{Q'_j final}{\beta'}}}, \qquad \textbf{[4]}$$

where Q'(*final*) is the final Q value computed at the end of the training phase, given the current α' and β' parameters. Given that no feedback is given during the test phase, Q' values were not expected to change after each trial. Thus, to increase the likelihood of the test phase responses, we will calculate the best fitting parameters α'_G, α'_L, β', of the Q' equation:

$$LLE(test) = \log\left(\prod_{test} P(test)_{i*,test}\right), \qquad \textbf{[5]}$$

where $i*$,*test* is the participants response in each trial in the test phase. The best fit parameters for each participant are those associated with the LLE value and are, again, predictive for a participant’s series of responses, now during the test phase.

3.6 Primary Analyses

To examine the main and interactive effects of BPD, Feedback type, and Emotion condition on learning outcome variables (i.e., gain learning accuracy, loss learning accuracy, high-conflict gain learning accuracy, high-conflict loss learning accuracy, gain learning rate, loss learning rate, stochasticity), we conducted multilevel linear models estimated with maximum likelihood using Mplus, v.8.1, statistical software (Muthén & Muthén, 2018), with outcomes assessed after each emotion condition (0 = neutral, 1 = negative) at Level 1 nested within individuals at Level 2. Because we only had two timepoints for each of our outcome variables (following the neutral and the negative mood inductions), we set the starting residual variance for each of our outcome variables using values generated by Mplus. For each outcome variable, five models were conducted: (1) a simple model with only emotion condition (0 = neutral, 1 = negative) at Level 1 as a predictor; (2) a model with only emotion condition at Level 1 and BPD criteria (grand-mean-centered) at Level 2 included as predictors; (3) a model with only emotion condition at Level 1 and feedback type (0 = nonsocial, 1 = social) at Level 2 included as predictors; (4) a model with emotion condition at Level 1, and BPD criteria and feedback type at Level 2 included as predictors; and (5) a model with emotion condition, BPD criteria, feedback type, and the BPD x feedback interaction as predictors.

3.6.1 Aim 1: BPD Criteria and Emotion on Learning Outcomes

Following the examination of our simple model (Model 1), with only emotion condition included as a predictor, we conducted a second model (Model 2) with emotion included at Level 1 and BPD criteria included at Level 2. For reference, the Level 1 and 2 formulas for Model 2 of the gain learning parameter:

Level 1: $Gain\ Learning\ Rate_{ij} = \beta_{0j} + \beta_{1j}(Emotion)_{ij} + r_{ij}$

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01}(BPD)_{ij} + u_{ij}$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}(BPD)_{ij} + u_{ij} \qquad \textbf{[6]}$$

3.6.2 Aim 2: BPD Criteria, Feedback Type, and Emotion on Learning Outcomes

In order to examine the main and interactive effects of BPD, Feedback type, and emotion condition on our learning outcomes, we examined Model 5, with all predictors added. For reference, the Level 1 and 2 formulas for Model 5 of the gain learning parameter:

Level 1: $Gain\ Learning\ Rate_{ij} = \beta_{0j} + \beta_{1j}(Emotion)_{ij} + r_{ij}$

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01}(BPD)_{ij} + \gamma_{02}(Feedback)_{ij} + \gamma_{03}(BPDxFeedback)_{ij} + u_{ij}$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}(BPD)_{ij} + \gamma_{12}(Feedback)_{ij} + \gamma_{13}(BPDxFeedback)_{ij} + u_{ij}$$

[7]

We first examined the γ_{03} and γ_{13} values to answer our primary question, whether BPD and Feedback would interact in predicting differences in learning accuracy, learning rate, and deterministic tendency. We then examined the main effects of BPD (γ_{01} and γ_{11}) and Feedback type (γ_{02} and γ_{12}) to further elucidate changes associated BPD criteria, when nonsocial feedback is provided, and difference between nonsocial and social feedback, for participants with an average number of BPD criteria.

CHAPTER 4

RESULTS

4.1 Preliminary Analyses

Preliminary analyses were conducted using IBM SPSS Statistics, Version 23. After examining descriptive statistics, all deterministic tendency (β) values were log 10 transformed due to high positive skewness and kurtosis. We also visually examined scatterplots of our predictor and primary outcome variables. Scatterplots revealed that there may be an interaction of BPD criteria and emotion on the gain and loss learning rates during the training phase and the gain learning rate during the test phase of the task; however, it appears that there may not be a significant interaction between BPD criteria and emotion on the learning accuracy variables. Descriptive statistics are reported in Table 2 and scatterplots are shown in Figures 3-5.

Based on a paired samples *t*-test comparing self-reported negative emotions after the neutral and negative emotion inductions, the negative mood induction was successful in eliciting stress in our participants, as self-reported negative emotions were higher after the stressful mood induction ($N = 124$; $M = 1.83$, $SD = 0.49$) than after the neutral mood induction ($N = 124$; $M = 1.33$, $SD = 0.32$; $t(123) = -12.80$; $p < .001$, $d = 1.24$).

In order to analyze the learning task, we excluded participants who did not exhibit adequate learning on the task, by excluding participants who did not select the most rewarding stimuli over the most punishing stimulus more than 50% of the time ($N = 21$; no BPD $n = 10$; subthreshold BPD $n = 3$; BPD $n = 9$), consistent with prior research (Cavanagh et al., 2011; Frank et al., 2005). There was a significant association between age and passing this learning threshold ($F(1,143) = 5.85$, $p = .017$), such that those who did not pass the learning threshold were significantly older (*M* = 26.90, *SD* = 9.14) than those who passed the learning threshold (*M* = 22.90, *SD* = 6.44). Two people who did not pass the learning threshold did not report their age. There was a nonsignificant association between the learning threshold and race/ethnicity ($\chi^2(5) = 5.79$, $p = .328$), sex ($\chi^2(2) = 0.16$, $p = .924$), or BPD diagnosis ($\chi^2(2) = 1.72$, $p = .423$). Overall, the participants in our study learned adequately, based on the average gain accuracy (on trials where choosing A is the optimal response) in the neutral condition (*M* = .72, *SD* = .23) and in the negative condition (*M* = .68, *SD* = .23) and on loss trials (where avoiding B is the optimal response) in the neutral condition (*M* = .69, *SD* = .21) and in the negative condition (*M* = .67, *SD* = .22). These values are similar to past research with this task (Cavanagh et al., 2010, 2011; Dixon-Gordon et al., 2018). In particular, comparable values were seen in neutral emotional conditions among healthy (gain *M* = 0.76, *SD* = 0.21; loss *M* = 0.74, *SD* = 0.21) and BPD participants (gain *M* = 0.68, *SD* = 0.21; loss *M* = 0.64, *SD* = 0.19). Likewise, comparable values were seen in negative emotional conditions among healthy (gain *M* = 0.61, *SD* = 0.20; loss *M* = 0.64, *SD* = 0.20) and BPD participants (gain *M* = 0.66, *SD* = 0.26; loss *M* = 0.55, *SD* = 0.23).

In terms of potential covariates, based on correlations between demographic features and learning outcomes, we examined associations between demographic features (i.e., sex, race, age, race/ethnicity) and primary study variables (i.e., learning accuracy, BPD criteria) in order to determine essential covariates to include. Age and female (vs. other) sex were both significantly correlated with lower test phase loss learning rate in the negative emotion condition (age: $r = -.19$, $p = .038$; female sex: $r = -.18$, $p = .044$), respectively), and majority race/ethnicity (vs. minority) was significantly correlated with higher training phase gain learning rate - neutral emotion condition ($r = .18$, $p = .039$), and test phase deterministic tendency, neutral emotion ($r = -.17$, $p = .047$). Additionally, majority race/ethnicity was significantly correlated with more BPD criteria ($r = .19$, $p = .024$). Finally, none of these demographic features were associated with the learning accuracy outcomes in the neutral or stressed conditions. Since none of these demographic features were consistently correlated with learning outcomes across the neutral and negative emotion conditions, no covariates were included in the primary analyses. See Tables 3 and 4 for full correlation matrix.

4.2 Primary Analyses

See Tables 5-14 for the results of all five multilevel linear models for each outcome variable.

4.2.1 Aim 1: BPD Criteria and Emotion on Learning Outcomes

Results reported below are from Model 2.

4.2.1.1 Training Phase

There was a marginal main effect of BPD criteria on the training phase gain learning rate, such that each additional BPD criterion is associated with a 0.02 unit decrease in gain learning rate in response to the neutral emotion condition ($SE = 0.01$, $p = .062$). Additionally, there was a nonsignificant effect of BPD in predicting the slope in Emotion condition in terms of the change in training phase gain learning rate from the neutral to negative mood induction ($p = .104$).

There was a nonsignificant main effect of BPD criteria on the training phase loss learning rate in response to the neutral emotion condition (p = .374). However, there was a significant effect of BPD in predicting the slope in Emotion condition in terms of the change in training phase loss learning rate from neutral to the negative mood induction, such that the difference in the loss learning rate between neutral and negative mood inductions is larger as the number of BPD criteria increases (γ_{11} = 0.04, *SE* = 0.01, p = .003).

There was a significant main effect of BPD criteria on training phase deterministic tendency, with each additional BPD criterion is associated with a 0.01 unit decrease in deterministic tendency (i.e., more deterministic responding) in response to the neutral emotion condition (*SE* = 0.01, p = .041). However, there was a nonsignificant effect of BPD in predicting the slope in Emotion condition in terms of the change in training phase deterministic tendency from the neutral to negative mood induction (p = .171).

4.2.1.2 Test Phase

There was a significant main effect of BPD criteria on the test phase gain learning rate, such that each additional BPD criterion is associated with a 0.03 unit decrease in gain learning rate (*SE* = 0.01, p = .029) in response to the neutral emotion condition. Additionally, there is a significant effect of BPD in predicting the Emotion slope in terms of the change in test phase gain learning rate from the neutral to negative mood induction, such that the difference in the gain learning rate between neutral and negative mood inductions is larger as the number of BPD criteria increases (γ_{11} = 0.05, *SE* = 0.02, *p* = .008).

There was a significant main effect of BPD criteria on the test phase loss learning rate, such that each additional BPD criterion is associated with a 0.03 unit increase in loss learning rate (*SE* = 0.01, *p* = .020) in response to the neutral emotion condition. However, there was a nonsignificant effect of BPD in predicting the Emotion slope in terms of the change in test phase loss learning rate from neutral to the negative mood induction (*p* = .258).

There was a significant main effect of BPD criteria on the test phase deterministic tendency in response to the neutral emotion condition, such that each additional BPD criterion is associated with a 0.02 unit decrease in deterministic tendency (i.e., more deterministic responding; *SE* = 0.01, *p* = .007). Further, there was a significant effect of BPD in predicting the Emotion slope in terms of the change in test phase deterministic tendency from the neutral to negative mood induction, such that the difference in deterministic tendency between neutral and negative mood inductions is larger as the number of BPD criteria increases (γ_{11} = 0.02, *SE* = 0.01, *p* = .013).

4.2.1.3 Learning Accuracy

There was a nonsignificant main effect of BPD criteria on gain learning accuracy (*p* = .858). Additionally, there was not a significant effect of BPD in predicting the Emotion slope in terms of the change in gain learning accuracy from neutral to the negative mood induction (*p* = .396). When looking at the high conflict trials, there was a nonsignificant main effect of BPD criteria on gain learning accuracy (*p* = .423) in response to the neutral emotion condition. However, there was a significant effect of BPD on Emotion slope in terms of the change in high conflict gain learning accuracy from neutral to the negative mood induction, such that the difference in the reward learning accuracy between neutral and negative mood inductions was smaller as the number of BPD criteria increases (γ_{11} = -0.02, *SE* = 0.01, *p* = .021).

There was a nonsignificant main effect of BPD criteria on loss learning accuracy in response to the neutral emotion condition (*p* = .608). Additionally, there was a nonsignificant effect of BPD in predicting the Emotion slope in terms of the change in loss learning accuracy from neutral to the negative mood induction (*p* = .582). Finally, when looking at high conflict trials, there was a nonsignificant main effect of BPD criteria on loss learning accuracy (*p* = .846) in response to the neutral emotion condition or on the Emotion slope in terms of the change in high conflict loss learning accuracy from neutral to the negative mood induction (*p* = .868).

4.2.2 Aim 2: BPD Criteria, Feedback Type, and Emotion on Learning Outcomes

Results reported below are from Model 5.

4.2.2.1 Training Phase

There was a nonsignificant BPD x Feedback interaction on the training phase deterministic tendency in response to the neutral emotion induction (*p* = .425) or the Emotion slope in terms of the change in deterministic tendency from the neutral to negative mood induction (*p* =.147). However, for those who received nonsocial feedback, there was a significant effect of BPD criteria on the training phase deterministic tendency in the neutral emotion condition, such that each additional BPD criterion was associated with a 0.02 unit decrease in deterministic tendency (*SE* = 0.01, *p* = .035). In addition, for those who received nonsocial feedback, there was a significant effect of BPD criteria on Emotion slope in terms of the difference between the deterministic tendency in the neutral to negative mood induction, such that each additional BPD criterion was associated with a smaller difference in deterministic tendency (γ_{01} = 0.02, *SE* = 0.01, *p* = .037). Finally, for those with an average number of BPD criteria, there was a significant effect of Feedback on Emotion slope in terms of the difference between the deterministic tendency in the neutral to negative mood induction, such that the negative emotion condition resulted in greater stochasticity in responding in the context of social feedback, but less stochastic responding in the context of nonsocial feedback such that the difference in deterministic tendency between neutral and negative mood inductions is smaller when the feedback type was social, rather than nonsocial (γ_{02} = 0.09, *SE* = 0.03, *p* = .011).

There was a significant interaction of BPD x Feedback on the training phase gain learning rate in response to the neutral condition (γ_{03} = 0.06, *SE* = 0.02, *p* = .013). Further, for those who received nonsocial feedback, there was a significant effect of BPD criteria on the training phase gain learning rate in the neutral emotion condition, such that each additional BPD criterion was associated with a 0.05 unit decrease in gain learning rate (*SE* = 0.02, *p* = .002). However, there was a nonsignificant effect of Feedback type on training phase gain learning rate in response to the neutral condition for individuals with an average number of BPD criteria (*p* = .621). In addition, there was a significant BPD x Feedback interaction on the Emotion slope between the gain learning rate in the neutral to negative mood induction (γ_{13} = -0.10, *SE* = 0.03, *p* = .002). For those who received nonsocial feedback, there was a significant effect of BPD on the Emotion slope in terms of the difference between the gain learning rate in the neutral to negative mood induction, such that each additional BPD criterion was associated with a larger difference in gain learning rate (γ_{11} = 0.07, *SE* = 0.02, *p* = .001). However, there was a nonsignificant effect of Feedback on the Emotion slope in terms of difference between the gain learning rate in the neutral to negative mood induction, for individuals with an average number of BPD criteria (*p* = .486).

There was a nonsignificant BPD x Feedback interaction on the training phase loss learning rate in response to the neutral condition (*p* = .531) or on Emotion slope in terms of the change in loss learning rate from the neutral to negative mood induction (*p* =.776). However, there was a significant effect of BPD on the Emotion slope such that, for those who received nonsocial feedback, each additional BPD criterion was associated with a smaller difference in loss learning rate from neutral to negative emotion inductions (γ_{11} = 0.04, *SE* = 0.02, *p* = .012).

4.2.2.2 Test Phase

There was a nonsignificant effect of the interaction between BPD and Feedback type on the training phase deterministic tendency in the neutral emotion condition (*p* = .262). However, there was a significant effect of the BPD x Feedback interaction on the Emotion slope in terms of change in deterministic tendency from the neutral to negative mood induction (γ_{13} = 0.03, *SE* = 0.02, *p* = .026). However, there was a nonsignificant effect of BPD criteria, for those who received nonsocial feedback (*p* = .673), or Feedback type, for those who had an average number of BPD criteria (p = .951) on the difference between neutral and negative mood deterministic tendency.

There was a nonsignificant BPD x Feedback interaction on the test phase gain learning rate in the neutral emotion condition (p = .534) or on the Emotion slope in terms of the change in gain learning rate from the neutral to negative mood induction (p =.296).

Additionally, there was a nonsignificant BPD x Feedback interaction on the test phase loss learning rate in the neutral emotion condition (p = .402) or on the Emotion slope in terms of the change in loss learning rate from the neutral to negative mood induction (p =.319).

4.2.2.3 Learning Accuracy

There was a nonsignificant BPD x Feedback interaction between on gain learning accuracy in the neutral emotion condition (p = .153) or on the Emotion slope in terms of the change in gain learning accuracy from the neutral to negative mood induction (p = .996). When looking at only the high conflict trials, there was also a nonsignificant BPD x Feedback interaction on the gain learning accuracy in the neutral emotion condition (p = .572) or on the Emotion slope in terms of the change in gain learning accuracy from the neutral to negative mood induction (p = .403). However, there was a significant effect of BPD criteria on the Emotion slope such that, for those who received nonsocial feedback, each additional BPD criterion was associated with a larger difference between gain learning accuracy in neutral versus negative emotion inductions (γ_{11} = -0.03, SE = 0.01, p = .020).

There was also a nonsignificant BPD x Feedback interaction on loss learning accuracy in the neutral emotion condition (p = .510) or on the Emotion slope in terms of the change in loss learning accuracy from the neutral to negative mood induction (p = .184). And again, when looking at only the high conflict trials, there was also a nonsignificant BPD x Feedback interaction on the loss learning accuracy in the neutral emotion condition (p = .488) or on the Emotion slope in terms of change in loss learning accuracy from the neutral to negative mood induction (p = .978).

CHAPTER 5

DISCUSSION

The overarching aim of this study was to harness reinforcement learning approaches to understand the link between BPD symptoms and decision-making deficits. Furthermore, we aimed to explore the role of emotions and social cues in the ability to learn from feedback. This line of work offers the hope of better understanding the sources of learning impairment and conditions under which learning deficits may occur. Several hypotheses guided the present work. First, replicating past work (Dixon-Gordon et al., 2018), we expected that BPD would be associated with worse performance on the learning task post-stressor, whereas this pattern is not expected to emerge among individuals with lower number of BPD criteria. Furthermore, we explored whether the tendency to misperceive social cues often seen in BPD (Dyck et al., 2008) led to greater alterations in learning in response to social feedback.

Results from the present study provide partial support for the hypothesis that negative emotions would interfere with learning in BPD. In particular, the negative emotion induction led to increases in loss learning rate based on training phase models among participants with greater BPD criteria. Additionally, the negative emotion induction led to increases in test phase models of gain learning rate among participants with higher BPD criteria. These findings are inconsistent with past work, wherein learning rates were blunted post stressor (Fineberg et al., 2018). Of note, cross-sectionally BPD was associated with higher loss and gain learning rates in general, so one interpretation of these findings is perhaps negative emotions lead participants with BPD to have a recency effect, wherein learning is not accumulated over time, but decisions are based more on the more recent feedback.

The interpretation of learning rates is complex – while some research shows that higher learning rates are linked to fewer errors (Dombrovski et al., 2010), other researchers have suggested that lower learning rates might be beneficial and lead to slow integration of information (Cavanagh et al., 2011). It may be that the interpretation of learning rates depends on the volatility of the environment – it maybe more optimal to integrate information from past outcomes over a longer period, rather than relying only on the most recent observations (Scholl & Klein-Flügge, 2018). In the present study, gain learning rates were somewhat inconsistently associated with some accuracy outcomes based on cross-sectional associations. Specifically, gain learning rates in the neutral (for test phase; $r = -.26$, $p < .01$) and negative (for training phase; $r = -.21$, $p < .05$) emotion conditions were inversely associated with overall gain accuracy, and in the negative (for test phase) condition was inversely associated with high conflict gain accuracy ($r = -.23$, $p < .05$). Conversely, however, the test gain learning rate in the negative condition was *positively* associated with loss accuracy ($r = .34$, $p < .01$) and high conflict loss accuracy ($r = .30$, $p < .01$) in the negative condition. Thus, for the present task, lower learning rates for gain and higher learning rates for loss may be most optimal.

The results of the examination of BPD on learning accuracy provided only partial support for our hypotheses. In particular, BPD was associated with worsening high conflict gain learning accuracy after the negative emotion induction. Although this finding mirrors past work suggesting that negative emotions worsens high conflict learning accuracy (Cavanagh et al., 2011), and high conflict loss learning accuracy in

BPD in particular (Dixon-Gordon et al., 2018), in the present study this pattern of effects was circumscribed to gain learning. Other work has pointed to impairments in gain learning among people with suicide attempt histories (Tsypes et al., 2020), which may overlap in large part with the BPD sample, providing support for reward learning deficits in particular in BPD. Although we did not find associations between BPD and loss learning, visual observations of graphical plots of the data revealed that learning accuracy for people with BPD was lower in both the neutral and negative conditions, especially for high conflict trials, although this effect was not significant. It is worth highlighting that the present study examined BPD criteria dimensionally, and therefore may detect findings that would not be discernable in terms of overall group differences. In addition, whereas past research has compared individuals with BPD to a healthy (asymptomatic) control group (Dixon-Gordon et al., 2018), we did not exclude participants with other disorders. As a result, it is possible that we did not identify small but perhaps meaningful differences between groups.

Although exploratory, we also examined the interaction of BPD and emotion condition on stochastic versus deterministic learning approaches. Participants with elevated BPD criteria responded more deterministically in the neutral condition, and the negative emotion induction led to more stochastic responses based on test-phase models. These data are consistent with some research that shows more stochastic responding among participants with mood and anxiety disorders when compared to healthy controls (Aylward et al., 2019), and inconsistent with other research that shows similar patterns of random exploration between those with or without psychopathology (Rothkirch et al., 2017; Wiehler et al., 2021). The pattern of findings for with participants with elevated

BPD criteria in our sample is the opposite of what we saw for participants low in BPD criteria; these participants responded more stochastically during the neutral emotion, then became more deterministic when stressed. Nevertheless, these findings are consistent with generally less rule-governed behavior and greater impulsivity under times of stress among participants with elevated BPD features (Chapman et al., 2008, 2010).

It is worth mentioning that we obtained a different pattern of findings in terms of the training phase versus test phase models of learning. In the training phase of the learning task, feedback (i.e., gain or loss) is provided after specific pairs of stimuli are presented (Cavanagh et al., 2011; Frank et al., 2005), and learning parameters are updated accordingly. Thus, this phase can allow for an understanding of learning acquisition. Further, parameters based on these models may reflect rapid adjustments in response to changing contingencies, and working memory, and may be associated with activity in the prefrontal cortex (Frank et al., 2007). However, in the test phase of the learning task, novel choices are presented, no feedback is provided, and learning parameters are not updated from trial to trial. Instead, this phase allows for an understanding of learning generalization, where what was learnt from feedback during the training phase is generalized to novel choices. Thus, parameters generated from models fit to the test phase may reflect ingrained, habitual, or long-term learning, and may be associated with activity in the basal ganglia (Frank et al., 2007). In past work, early learning acquisition was not linked to BPD group (Maurex et al., 2009); yet, learning acquisition was specifically influenced by stimulus arousal in one study (Paret et al., 2016). Thus, we examined models based on both training and test phase in the present study. From this standpoint, negative emotions seemed to increase loss learning rates in BPD through a lens of more rapid adjustments to contingencies, whereas negative emotions increased gain learning rates in BPD, reflecting more habitual behaviors.

Expanding the focus on learning in BPD to different types of feedback, the present study examined the role of facial feedback on learning outcomes. There were less data to guide us in understanding the influence of social feedback on learning, yet some research has shown increased weighting of social cues in BPD (Fineberg et al., 2018). This increased weighting of social cues may enhance learning from such cues in BPD, whereas the potential to misinterpret these cues may impair such learning. As such, we hypothesized that BPD symptoms would interact with social conditions in predicting (a) poorer learning accuracy (especially on more difficult trials) and (b) impaired learning rates, with worse outcomes in social (vs. non-social) conditions. Our results did not provide support for this hypothesis. However, these data suggest that, for people low in BPD features, the highest learning rate was seen in the neutral condition in response to nonsocial feedback. Social feedback made gain learning look more similar to learning under negative conditions for those with lower BPD features, whereas this divergence was not seen among those with high BPD features. Thus, it is possible that elevated learning rates are seen in this context for those low in BPD features because this is essentially a "low-volatility" or less complex learning environment (Scholl & Klein-Flügge, 2018). Those high in BPD features may not show this normative divergence because they may experience these neutral contexts as high volatility, as research has shown a negative bias in their interpretation of neutral social situations (De Panfilis et al., 2019; Lis & Bohus, 2013).

We did not have an a priori hypothesis for the interaction of feedback on BPD for deterministic tendency. These data showed that BPD, feedback type, and emotion condition interacted, such that social feedback was associated with greater difference between the neutral and negative emotion conditions. Whereas participants with elevated BPD criteria had increased stochasticity of responses to the negative emotion induction, participants with lower BPD features had increases in deterministic tendencies. Overall, this pattern of findings was more divergent between social and nonsocial feedback under neutral conditions for those with lower BPD features, suggesting perhaps these individuals were weighing social cues less heavily.

5.1 Limitations and Future Directions

This study is not without its limitations. First, our sample was recruited in the western Massachusetts region, and relatively homogeneous with regard to race and ethnicity. Therefore, our findings may not generalize to other clinical samples. Second, given the high rates of co-occurrence of BPD with other psychological disorders (Zanarini et al., 2004), some of the findings associated with BPD may be due to co-occurring conditions. However, because we examined BPD continuously, consistent with dimensional models of this disorder (Trull et al., 2011), and did not exclude participants based on psychopathology, suggesting that any findings associated with BPD may be specific. That said, the fact that we had no healthy control comparison per se may have reduced our ability to detect differences that may exist, and likewise limits comparability with other research (Dixon-Gordon et al., 2018; Fineberg et al., 2018). Third, we used a learning task with relatively few trials. This is important, given past work showing that individuals with BPD tend towards an impulsive and careless problem solving approach (Dixon-Gordon et al., 2011). Yet, this may also limit the reliability of the learning parameter estimates. Given the limited number of trials in the learning task, it is possible that our models will not allow us to detect small but meaningful differences. Fourth, we examined learning on one particular day, and therefore may not have detected patterns of learning, or how learning processes adapt to changing environments. Future research could use reinforcement learning models to examine learning from feedback at multiple timepoints. Finally, although we intentionally used a fixed order of mood inductions to reduce carry over effect, it is still possible that we may see a fatigue or practice effect on the second administration of the learning task, which would make the results appear that performance changed due to the negative mood induction, when this may not be the case. It is worth noting that past work with this task has suggested that practice effects with this task may be small (Cavanagh et al., 2011). Future research should consider other methodological ways to address this issue.

5.2 Implications

Despite limitations, this study extends current literature examining deficits in learning and decision-making. We made use of a novel approach through the use of reinforcement learning computational modeling, as these methods are still emerging and have only very recently been used with BPD populations. We are also beginning to fill an essential gap in the literature, by examining decision-making and learning deficits among people with BPD and the differences between social and nonsocial feedback. Overall, this study helps explain why people with BPD tend to engage in self-destructive and risky behaviors, despite the negative consequences associated with these behaviors.

Findings from this study suggest that negative emotions uniquely affect learning rates and accuracy in responding to inconsistent positive feedback in BPD. Furthermore, social feedback leads to more normalized learning rates for people with BPD, even when distressed. By understanding the specific contexts in which people with BPD experience the greatest difficulty learning from feedback, we can determine the mechanisms through which certain symptoms of BPD might develop. For instance, these data suggest that positive feedback may be harder for people with BPD to process when they are upset. In addition, given the heterogeneity of specific BPD criteria, future analyses can examine whether certain criteria have stronger associations with learning impairments than others. This would not only allow for a better understanding of the individual symptoms associated with BPD, but it would bolster our understanding of the development of the disorder and streamline interventions to more effectively determine treatment targets.

In addition, understanding the specific contexts in which people with BPD experience the least difficulty from feedback allows for important clinical implications. For instance, social feedback appears to more effective for people with BPD, even when they are distressed. Given that psychotherapy is most often a social context, providing therapists with a research-based expectation of how their clients might respond to rewards or punishments will allow therapists to structure treatment in a more effective way. Furthermore, preliminary data suggest that learning signatures can indicate how well patients with anxiety disorders will respond well to psychological interventions (Culver et al., 2015). Therefore, it is worth examining these learning profiles as potential predictors of treatment outcome in BPD, thereby improving resource allocation. Pending replication, the present study could have important implications for the research and treatment of BPD.

Table 1

Demographic Characteristics of Our Sample

	M(*SD*) or *N*(%)
Age	22.90(6.44)
Sex	
Female	107(81.7%)
Male	19(14.5%)
Other or Declined to Answer	4(3.9%)
Gender Identity	80.44(33.98)
Race/Ethnicity	
White	83(63.4%)
Asian/Southeast Asian	22(16.8%)
Black/African American	8(6.1%)
Hispanic/Latinx	1(0.8%)
Multiracial	11(8.4%)
Other or Declined to Answer	6(4.6%)
Marital Status	
Single (never married, divorced, widowed)	111(84.7%)
Living with a partner	13(9.9%)
Legally partnered	4(3.1%)
Family Yearly Income	$54,634.47($33,927.95)
Education	
High school/GED	9(6.8%)
Some college/technical school	83(68.8%)
College graduate	16(12.2%)
Some graduate school	10(7.6%)
Graduate degree	10(7.6%)
Employment Status	
Unemployed	14(10.7%)
Employed Part-time	23(17.6%)
Employed Full-time	22(16.8%)
Part-time student	4(3.1%)
Full-time student	65(49.6%)
Psychopathology History - Lifetime	
Major Depressive Disorder	89(67.9%)
Bipolar I Disorder	6(4.6%)
Panic Disorder	31(23.7%)
Agoraphobia	16(12.2%)
Social Phobia	34(26.0%)
Generalized Anxiety Disorder	24(18.3%)
Obsessive Compulsive Disorder	7(5.3%)
Posttraumatic Stress Disorder	39(29.8%)
Alcohol Use Disorder	68(51.9%)
Substance Use Disorder	58(44.3%)
Borderline Personality Disorder Criteria	2.80(2.54)

Note. Gender identity was reported on a continues scale where 0 indicated masculine and 100 indicated feminine; *M* and *SD* were reported.

Table 2

Descriptive Statistics of Primary Study Variables

	Neutral Emotion Condition			Negative Emotion Condition		
	M(*SD*)	Skewness (*SE*)	Kurtosis (*SE*)	*M*(*SD*)	Skewness (*SE*)	Kurtosis (*SE*)
Learning Parameters:						
Training Phase:						
Deterministic Tendency	0.58 (1.37)	5.68 (.21)	34.96 (.42)	0.51 (1.35)	5.99 (.21)	38.73 (.43)
Gain Learning Rate	0.31 (.35)	0.95 (.21)	-0.56 (.42)	0.38 (.38)	0.59 (.21)	-1.27 (.43)
Loss Learning Rate	0.30 (.32)	0.81 (.21)	-0.72 (.42)	0.27 (.30)	1.09 (.21)	0.05 (.42)
Test Phase:						
Deterministic Tendency	0.51 (1.72)	5.22 (.21)	26.54 (.42)	0.49 (1.52)	5.88 (.21)	34.65 (.43)
Gain Learning Rate	0.32 (.39)	0.81 (.21)	-1.07 (.42)	0.41 (.41)	0.40 (.21)	-1.53 (.43)
Loss Learning Rate	0.23 (.34)	1.36 (.21)	0.34 (.42)	0.28 (.36)	1.11 (.21)	-0.36 (.43)
Learning Accuracy:						
Gain Learning	0.72 (.23)	-0.78 (.21)	-0.09 (.42)	0.68 (.23)	-0.46 (.21)	-0.55 (.43)
Loss Learning	0.69 (.21)	-0.67 (.21)	0.24 (.42)	0.67 (.22)	-0.22 (.21)	-0.74 (.43)
High Conflict Gain Learning	0.62 (.21)	-0.52 (.21)	-0.14 (.42)	0.59 (.23)	-0.12 (.21)	-0.48 (.43)
High Conflict Loss Learning	0.58 (.24)	-0.24 (.21)	-0.58 (.42)	0.57 (.23)	-0.08 (.21)	-0.58 (.43)

Note: The reported values for deterministic tendency in both the training and test phase and in both the negative and neutral conditions were log10 transformed to adjust for high positive skewness and kurtosis. Transformed values: Neutral training phase β (*M* = 0.14, *SD* = .17, Skewness = 3.15, Kurtosis = 12.73); Negative training phase β (*M* = .13, *SD* = .17; Skewness = 3.52, Kurtosis = 15.16); Neutral test phase β (*M* =.10, *SD* = .19; Skewness = 4.06, Kurtosis = 17.38); and Negative test phase β (*M* = .11, *SD* = .17, Skewness = 4.20, Kurtosis = 19.93).

Table 3

Correlations of Primary Outcome Variables and Possible Covariates, Part 1

	M(*SD*) or *N*(%)	1	2	3	4	5	6	7	8	9	10	11	12
1. Age	22.90(6.44)	--											
2. Race/Ethnicity - White	91(69.5%)	-.05	--										
3. Sex - Female	107(81.7%)	-.17	.06	--									
4. BPD Criteria	2.80(2.54)	.12	.19*	.01	--								
5. Training Deterministic Tendency, neutral	0.14(0.17)	-.12	-.05	.01	-.18*	--							
6. Training Deterministic Tendency, negative	0.13(0.17)	-.004	.004	.003	-.04	.29**	--						
7. Training Gain Learning Rate, neutral	.31(.35)	-.16	.18*	-.03	-.16	.41**	.15	--					
8. Training Gain Learning Rate, negative	.38(.38)	-.03	.04	.11	.04	.10	.30**	.07	--				
9. Training Loss Learning Rate, neutral	.30(.32)	-.06	.03	-.04	-.08	-.02	-.03	.09	-.04	--			
10. Training Loss Learning Rate, negative	.27(.30)	.10	.04	.05	.26*	-.15	-.06	.001	-.31**	.19*	--		
11. Test Deterministic Tendency, neutral	0.10(0.19)	-.10	-.17*	-.07	-.23*	.48**	.27**	.09	.15	.19*	-.20*	--	
12. Test Deterministic Tendency, negative	0.11(0.17)	-.03	.12	-.01	.03	.22*	.61**	.25**	.10	.14	.08	.25**	--
13. Test Gain Learning Rate, neutral	.32(.39)	.03	-.10	-.06	-.19*	-.05	.08	.03	.02	.19*	-.04	.26**	.0
14. Test Gain Learning Rate, negative	.41(.41)	-.05	.112	.11	.15	-.06	-.09	.07	.05	.03	.01	-.09	.1
15. Test Loss Learning Rate, neutral	.23(.24)	-.11	.07	.13	.20*	.02	.30**	.13	.01	.19*	.19*	.04	.23
16. Test Loss Learning Rate, negative	.228(.36)	-.19*	.05	-.18*	.05	.03	.08	.10	.10	.03	.11	.02	.24
17. Gain Learning Accuracy, neutral	.72(.23)	-.01	-.02	-.02	.02	-.24**	.01	-.02	-.06	.07	.13	-.36**	.0
18. Gain Learning Accuracy, negative	.68(.23)	-.14	.13	.09	-.09	-.14	-.36**	-.03	-.21*	-.004	-.001	-.12	-.33
19. Loss Learning Accuracy, neutral	.69(.21)	.06	.11	.03	-.05	-.23**	-.11	-.12	-.05	-.07	-.07	-.22*	-.0
20. Loss Learning Accuracy, negative	.67(.22)	.01	.07	.05	.03	-.10	-.23**	-.16	-.15	.05	.06	-.10	-.26
21. High Conflict Gain Learning Accuracy, neutral	.63(.21)	-.08	-.06	-.01	.07	-.19*	.05	-.08	.03	.11	.12	-.21*	.0
22. High Conflict Gain Learning Accuracy, negative	.59(.23)	-.11	.05	.05	-.20*	-.14	-.21*	-.02	-.16	-.06	-.06	-.06	-.1
23. High Conflict Loss Learning Accuracy, neutral	.58(.24)	-.05	.04	-.03	-.02	-.16	-.03	-.12	-.04	-.05	-.08	-.17	.1
24. High Conflict Loss Learning Accuracy, negative	.57(.23)	.08	-.10	.01	.003	-.03	-.05	-.15	-.01	-.02	.02	-.06	-.0

Note. *$p < .05$, **$p < .01$

Table 4

Correlations of Primary Outcome Variables and Possible Covariates, Part 2

	M(*SD*) or *N*(%)	13	14	15	16	17	18	19	20	21	22	23	24
1. Age	22.90(6.44)												
2. Race/Ethnicity - White	91(69.5%)												
3. Sex - Female	107(81.7%)												
4. BPD Criteria	2.80(2.54)												
5. Training Deterministic Tendency, neutral	0.14(0.17)												
6. Training Deterministic Tendency, negative	0.13(0.17)												
7. Training Gain Learning Rate, neutral	.31(.35)												
8. Training Gain Learning Rate, negative	.38(.38)												
9. Training Loss Learning Rate, neutral	.30(.32)												
10. Training Loss Learning Rate, negative	.27(.30)												
11. Test Deterministic Tendency, neutral	0.10(0.19)												
12. Test Deterministic Tendency, negative	0.11(0.17)												
13. Test Gain Learning Rate, neutral	.32(.39)	--											
14. Test Gain Learning Rate, negative	.41(.41)	-.11	--										
15. Test Loss Learning Rate, neutral	.23(.24)	.13	.08	--									
16. Test Loss Learning Rate, negative	.228(.36)	-.02	.05	-.002	--								
17. Gain Learning Accuracy, neutral	.72(.23)	-.26**	.09	.05	-.05	--							
18. Gain Learning Accuracy, negative	.68(.23)	-.03	-.16	-.14	-.09	.09	--						
19. Loss Learning Accuracy, neutral	.69(.21)	.06	-.14	-.09	-.10	.06	.11	--					
20. Loss Learning Accuracy, negative	.67(.22)	-.14	.34**	-.04	-.14	-.03	-.03	-.13	--				
21. High Conflict Gain Learning Accuracy, neutral	.63(.21)	-.16	.03	.17	-.08	.69**	-.01	.16	-.06	--			
22. High Conflict Gain Learning Accuracy, negative	.59(.23)	.07	-.23*	-.17	-.04	.12	.75**	.26**	-.12	.06	--		
23. High Conflict Loss Learning Accuracy, neutral	.58(.24)	.06	-.12	-.04	-.07	.11	.01	.74**	-.14	.28**	.21*	--	
24. High Conflict Loss Learning Accuracy, negative	.57(.23)	-.14	.30**	-.05	-.09	.04	-.04	-.08	.71**	-.08	-.03	-.08	--

Note. *$p < .05$, **$p < .01$

Table 5

Multilevel Models of Gain Learning Rate (αG) in the Training Phase of the Learning Task

	Model 1			Model 2			Model 3			Model 4			Model 5		
	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*
Within Person:															
Intercept	0.31	0.03	<.001**	0.31	0.03	<.001**	0.32	0.04	<.001**	0.32	0.04	<.001**	0.33	0.04	<.001**
Emotion	0.07	0.04	.100	0.07	0.04	.099	0.10	0.06	.090	0.10	0.06	.094	0.1	0.06	.101
Between Person:															
BPD criteria				-0.02	0.01	.062				-0.02	0.01	.060	-0.05	0.02	.002*
BPD x Emotion				0.03	0.02	.104				0.03	0.02	.112	0.07	0.02	.001*
Feedback type							-0.03	0.06	.653	-0.03	0.06	.624	-0.03	0.06	.621
Feedback x Emotion							-0.06	0.09	.461	-0.06	0.09	.482	-0.06	0.08	.486
BPD x Feedback													0.06	0.02	.013*
BPD x Feedback x Emotion													-0.10	0.03	.002*

Note. The residual variance in the training phase gain learning rate was set at 0.05494. Emotion was coded such that 0 = neutral, 1 = negative. Feedback was coded so that nonsocial = 0, social = 1. BPD criteria centered at grand mean.

Table 6

Multilevel Models of Loss Learning Rate (αL) in the Training Phase of the Learning Task

	Model 1			Model 2			Model 3			Model 4			Model 5		
	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*
Within Person:															
Intercept	0.30	0.03	<.001**	0.30	0.03	<.001**	0.32	0.04	<.001**	0.31	0.04	<.001**	0.32	0.04	<.001**
Emotion	-0.03	0.03	.401	-0.03	0.03	.352	-0.08	0.05	.096	-0.09	0.05	.063	-0.09	0.05	.063
Between Person:															
BPD criteria				-0.01	0.01	.374				-0.01	0.01	.370	-0.02	0.01	.276
BPD x Emotion				0.04	0.01	.003				0.04	0.01	.002*	0.04	0.02	.012*
Feedback type							-0.02	0.06	.681	-0.02	0.06	.668	-0.02	0.06	.669
Feedback x Emotion							0.10	0.07	.134	0.11	0.07	.094	0.11	0.07	.094
BPD x Feedback													0.01	0.02	.531
BPD x Feedback x Emotion													-0.01	0.03	.776

Note. The residual variance in the training phase loss learning rate was set at 0.03900. Emotion was coded such that 0 = neutral, 1 = negative. Feedback was coded so that nonsocial = 0, social = 1. BPD criteria centered at grand mean.

Table 7

Multilevel Models of Deterministic Tendency (β) in the Training Phase of the Learning Task

	Model 1			Model 2			Model 3			Model 4			Model 5		
	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*
Within Person:															
Intercept	0.15	0.02	<.001**	0.15	0.02	<.001**	0.17	0.02	<.001**	0.17	0.02	<.001**	0.16	0.02	<.001**
Emotion	-0.02	0.02	.296	-0.02	0.02	.291	-0.06	0.03	.013*	-0.06	0.02	.011*	-0.06	0.02	.009*
Between Person:															
BPD criteria				-0.01	0.01	.041*				-0.01	0.01	.037*	-0.02	0.01	.035*
BPD x Emotion				0.01	0.01	.171				0.01	0.01	.136	0.02	0.01	.037*
Feedback type							-0.04	0.03	.138	-0.05	0.03	.122	-0.05	0.03	.122
Feedback x Emotion							0.08	0.04	.015*	0.09	0.03	.013*	0.09	0.03	.011*
BPD x Feedback													0.01	0.01	.425
BPD x Feedback x Emotion													-0.02	0.01	.147

Note. The residual variance in the training phase deterministic tendency was set at 0.05494. Emotion was coded such that 0 = neutral, 1 = negative. Feedback was coded so that nonsocial = 0, social = 1. BPD criteria centered at grand mean.

Table 8

Multilevel Models of Gain Learning Rate (αG) in the Test Phase of the Learning Task

	Model 1			Model 2			Model 3			Model 4			Model 5		
	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*
Within Person:															
Intercept	0.32	0.03	<.001**	0.32	0.03	<.001**	0.30	0.05	<.001**	0.31	0.05	<.001**	0.31	0.05	<.001**
Emotion	0.09	0.05	.068	0.09	0.05	.065	0.17	0.07	.021*	0.16	0.07	.022*	0.16	0.07	.020*
Between Person:															
BPD criteria				-0.03	0.01	.029*				-0.03	0.01	.030*	-0.02	0.02	.219
BPD x Emotion				0.05	0.02	.008*				0.05	0.02	.009*	0.03	0.03	.200
Feedback type							0.03	0.07	.698	0.02	0.07	.723	0.02	0.07	.724
Feedback x Emotion							-0.14	0.10	.161	-0.14	0.10	.173	-0.14	0.10	.167
BPD x Feedback													-0.02	0.03	.534
BPD x Feedback x Emotion													0.04	0.04	.296

Note. The residual variance in the test phase gain learning rate was set at 0.06648. Emotion was coded such that 0 = neutral, 1 = negative. Feedback was coded so that nonsocial = 0, social = 1. BPD criteria centered at grand mean.

Table 9

Multilevel Models of Loss Learning Rate (αL) in the Test Phase of the Learning Task

	Model 1			Model 2			Model 3			Model 4			Model 5		
	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*
Within Person:															
Intercept	0.23	0.03	<.001**	0.23	0.03	<.001**	0.21	0.04	<.001**	0.21	0.04	<.001**	0.21	0.04	<.001**
Emotion	0.05	0.04	.284	0.05	0.04	.287	0.05	0.06	.393	0.05	0.06	.393	0.06	0.06	.357
Between Person:															
BPD criteria				0.03	0.01	.020*				0.03	0.01	.019*	0.02	0.02	.222
BPD x Emotion				-0.02	0.02	.258				-0.02	0.02	.262	-0.04	0.02	.127
Feedback type							0.05	0.06	.404	0.05	0.06	.371	0.05	0.06	.368
Feedback x Emotion							-0.01	0.09	.880	-0.01	0.09	.873	-0.02	0.09	.845
BPD x Feedback													0.02	0.02	.402
BPD x Feedback x Emotion													0.03	0.03	.319

Note. The residual variance in the test phase loss learning rate was set at 0.05140. Emotion was coded such that 0 = neutral, 1 = negative. Feedback was coded so that nonsocial = 0, social = 1. BPD criteria centered at grand mean.

Table 10

Multilevel Models of Deterministic Tendency (β) in the Test Phase of the Learning Task

	Model 1			Model 2			Model 3			Model 4			Model 5		
	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*
Within Person:															
Intercept	0.10	0.02	<.001**	0.10	0.02	<.001**	0.09	0.02	<.001**	0.09	0.02	<.001**	0.09	0.02	<.001**
Emotion	0.01	0.02	.642	0.01	0.02	.648	0.01	0.03	.700	0.01	0.03	.739	0.01	0.03	.677
Between Person:															
BPD criteria				-0.02	0.01	.007*				-0.02	0.01	.008*	-0.01	0.01	.200
BPD x Emotion				0.02	0.01	.013*				0.02	0.01	.012*	.004	0.01	.673
Feedback type							0.03	0.03	.369	0.03	0.03	.383	0.03	0.03	.382
Feedback x Emotion							-0.004	0.04	.925	-0.001	0.04	.976	-0.002	0.04	.951
BPD x Feedback													-0.01	0.01	.262
BPD x Feedback x Emotion													0.03	0.02	.026*

Note. The residual variance in the test phase deterministic tendency was set at 0.01256. Emotion was coded such that 0 = neutral, 1 = negative. Feedback was coded so that nonsocial = 0, social = 1. BPD criteria centered at grand mean.

Table 11

Multilevel Models of Gain Learning Accuracy on the Learning Task

	Model 1			Model 2			Model 3			Model 4			Model 5		
	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*
Within Person:															
Intercept	0.72	0.02	<.001**	0.72	0.02	<.001**	0.72	0.03	<.001**	0.72	0.03	<.001**	0.72	0.03	<.001**
Emotion	-0.04	0.03	.135	-0.04	0.03	.139	-0.01	0.04	.731	-0.01	0.04	.761	-0.01	0.04	.788
Between Person:															
BPD criteria				0.001	0.01	.858				0.001	0.01	.856	-0.01	0.01	.423
BPD x Emotion				-0.01	0.01	.396				-0.01	0.01	.370	-0.01	0.01	.487
Feedback type							0.01	0.04	.895	0.01	0.04	.893	0.01	0.04	.889
Feedback x Emotion							-0.05	0.05	.318	-0.06	0.05	.299	-0.06	0.05	.288
BPD x Feedback													0.02	0.02	.153
BPD x Feedback x Emotion													0.00	0.02	.996

Note. The residual variance in the reward learning accuracy was set at 0.02229. Emotion was coded such that 0 = neutral, 1 = negative. Feedback was coded so that nonsocial = 0, social = 1. BPD criteria centered at grand mean.

Table 12

Multilevel Models of Loss Learning Accuracy on the Learning Task

	Model 1			Model 2			Model 3			Model 4			Model 5		
	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*
Within Person:															
Intercept	0.69	0.02	<.001**	0.69	0.02	<.001**	0.69	0.03	<.001**	0.69	0.03	<.001**	0.69	0.03	<.001**
Emotion	-0.02	0.03	.394	-0.02	0.03	.391	-0.01	0.04	.866	-0.01	0.04	.857	-0.01	0.04	.891
Between Person:															
BPD criteria				-0.004	0.01	.608				-0.004	0.01	.609	0.00	0.01	.961
BPD x Emotion				0.01	0.01	.582				0.01	0.01	.599	-0.01	0.02	.625
Feedback type							0.004	0.04	.916	0.004	0.04	.924	0.003	0.04	.925
Feedback x Emotion							-0.04	0.06	.543	-0.03	0.06	.552	-0.04	0.06	.538
BPD x Feedback													-0.01	0.02	.510
BPD x Feedback x Emotion													0.03	0.02	.184

Note. The residual variance in the loss learning accuracy was set at 0.01938. Emotion was coded such that 0 = neutral, 1 = negative. Feedback was coded so that nonsocial = 0, social = 1. BPD criteria centered at grand mean.

Table 13

Multilevel Models of High Conflict Gain Learning Accuracy on the Learning Task

	Model 1			Model 2			Model 3			Model 4			Model 5		
	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*
Within Person:															
Intercept	0.63	0.02	<.001**	0.63	0.02	<.001**	0.61	0.03	<.001**	0.61	0.03	<.001**	0.61	0.03	<.001**
Emotion	-0.03	0.03	.215	-0.03	0.03	.223	-0.01	0.04	.889	-0.002	0.04	0.964	0.00	0.04	.994
Between Person:															
BPD criteria				0.01	0.01	.423				0.01	0.01	.410	0.002	0.01	.803
BPD x Emotion				-0.02	0.01	.021*				-0.02	0.01	.019*	-0.03	0.01	.020*
Feedback type							0.04	0.04	.308	0.04	0.04	.300	0.04	0.04	.299
Feedback x Emotion							-0.06	0.06	.295	-0.06	0.05	.247	-0.06	0.05	.235
BPD x Feedback													0.01	0.02	.572
BPD x Feedback x Emotion													0.02	0.02	.403

Note. The residual variance in the high conflict gain learning accuracy was set at 0.02009. Emotion was coded such that 0 = neutral, 1 = negative. Feedback was coded so that nonsocial = 0, social = 1. BPD criteria centered at grand mean.

Table 14

Multilevel Models of High Conflict Loss Learning Accuracy on the Learning Task

	Model 1			Model 2			Model 3			Model 4			Model 5		
	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*	Effect	*SE*	*p*
Within Person:															
Intercept	0.58	0.02	<.001**	0.58	0.02	<.001**	0.57	0.03	<.001**	0.58	0.03	<.001**	0.58	0.03	<.001**
Emotion	-0.01	0.03	.679	-0.01	0.03	.678	0.03	0.04	.437	0.03	0.04	.438	0.03	0.04	.427
Between Person:															
BPD criteria				-0.002	0.01	.846				-0.002	0.01	.850	-0.01	0.01	.549
BPD x Emotion				0.002	0.01	.868				0.001	0.01	.917	0.001	0.02	.961
Feedback type							0.01	0.04	.783	0.01	0.04	.785	0.01	0.04	.784
Feedback x Emotion							-0.09	0.06	.134	-0.09	0.06	.134	-0.09	0.06	.131
BPD x Feedback													0.01	0.02	.488
BPD x Feedback x Emotion													0.01	0.02	.978

Note. The residual variance in the high conflict loss learning accuracy was set at 0.02294. Emotion was coded such that 0 = neutral, 1 = negative. Feedback was coded so that nonsocial = 0, social = 1. BPD criteria centered at grand mean.

Figure 1

Forced Choice Probabilistic Learning Task (Frank et al., 2005)

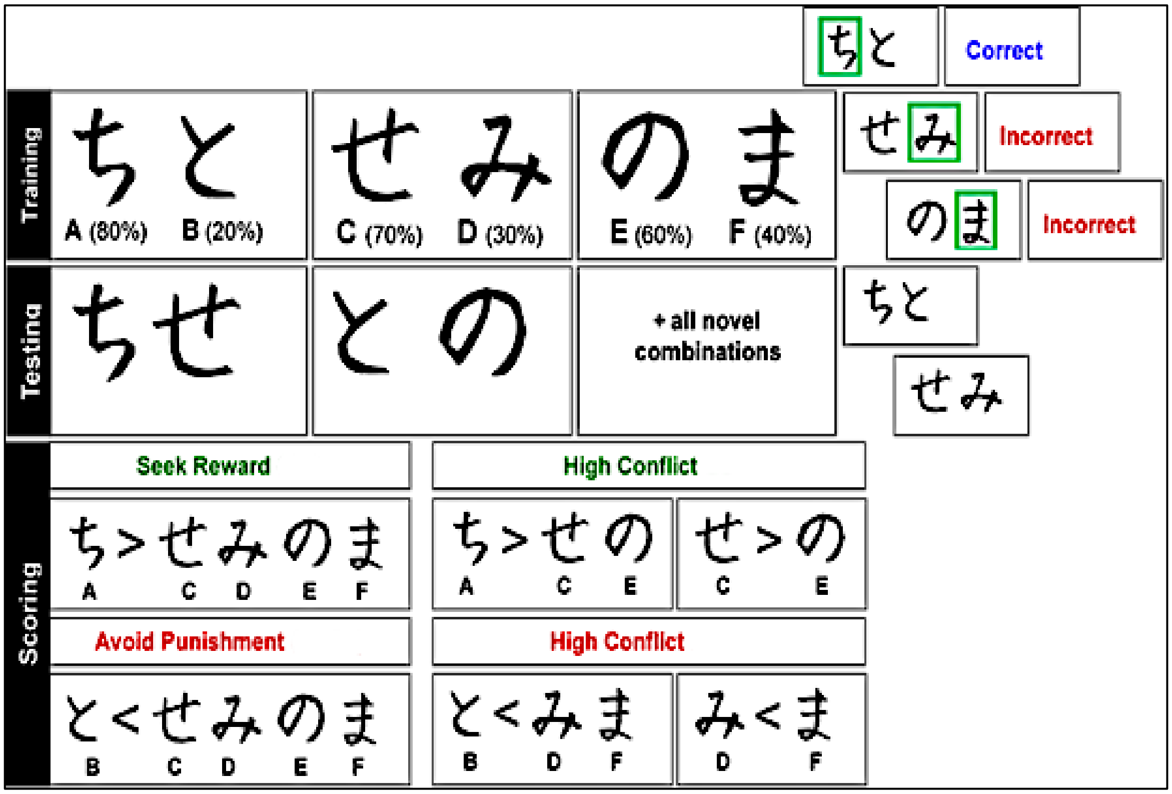


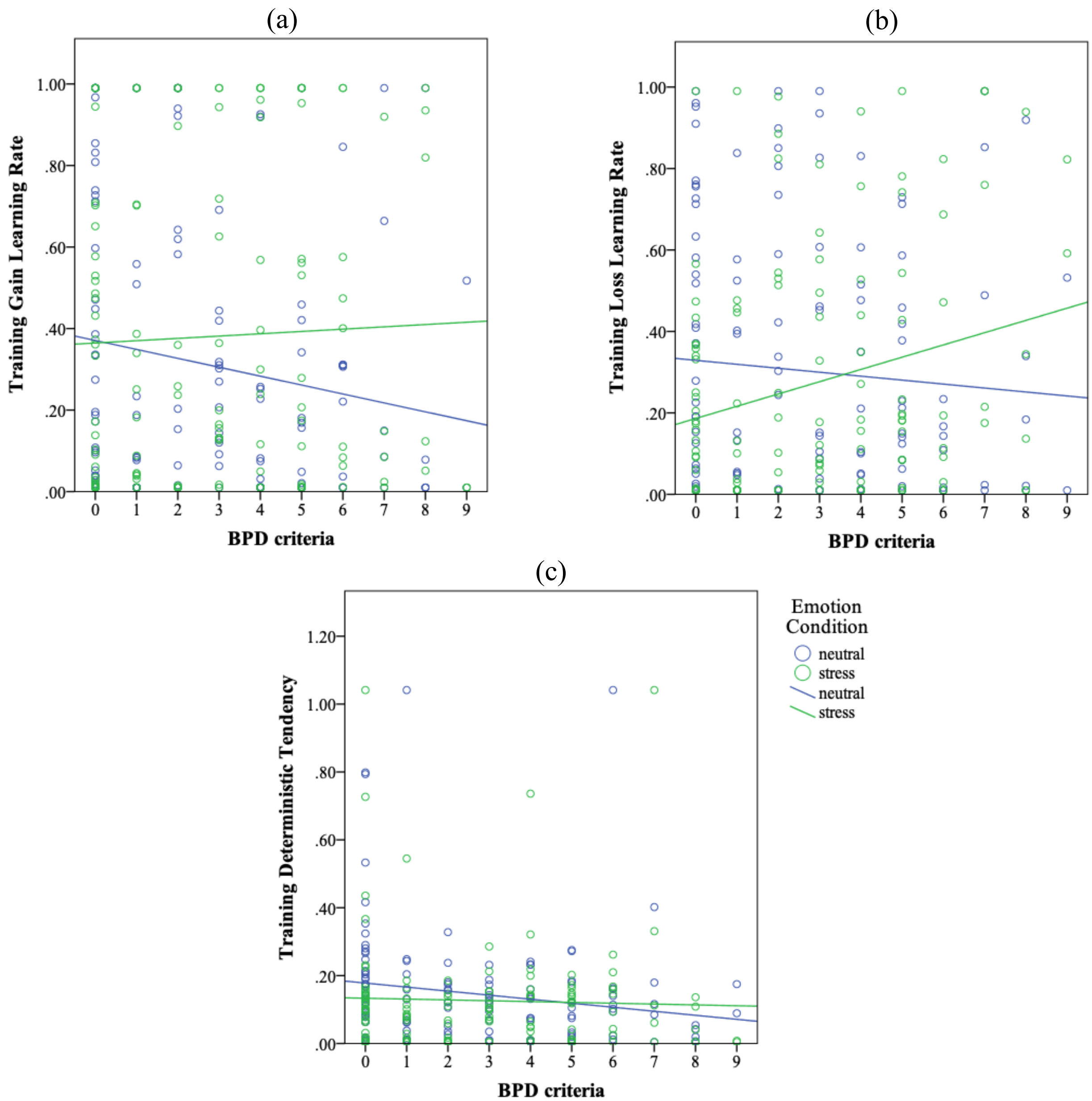
Figure 2

Examples of Faces Used in Social Feedback Condition (Tottenham et al., 2009)

Note. The image on the left indicated an incorrect response, while the image on the right indicated a correct response

Figure 3

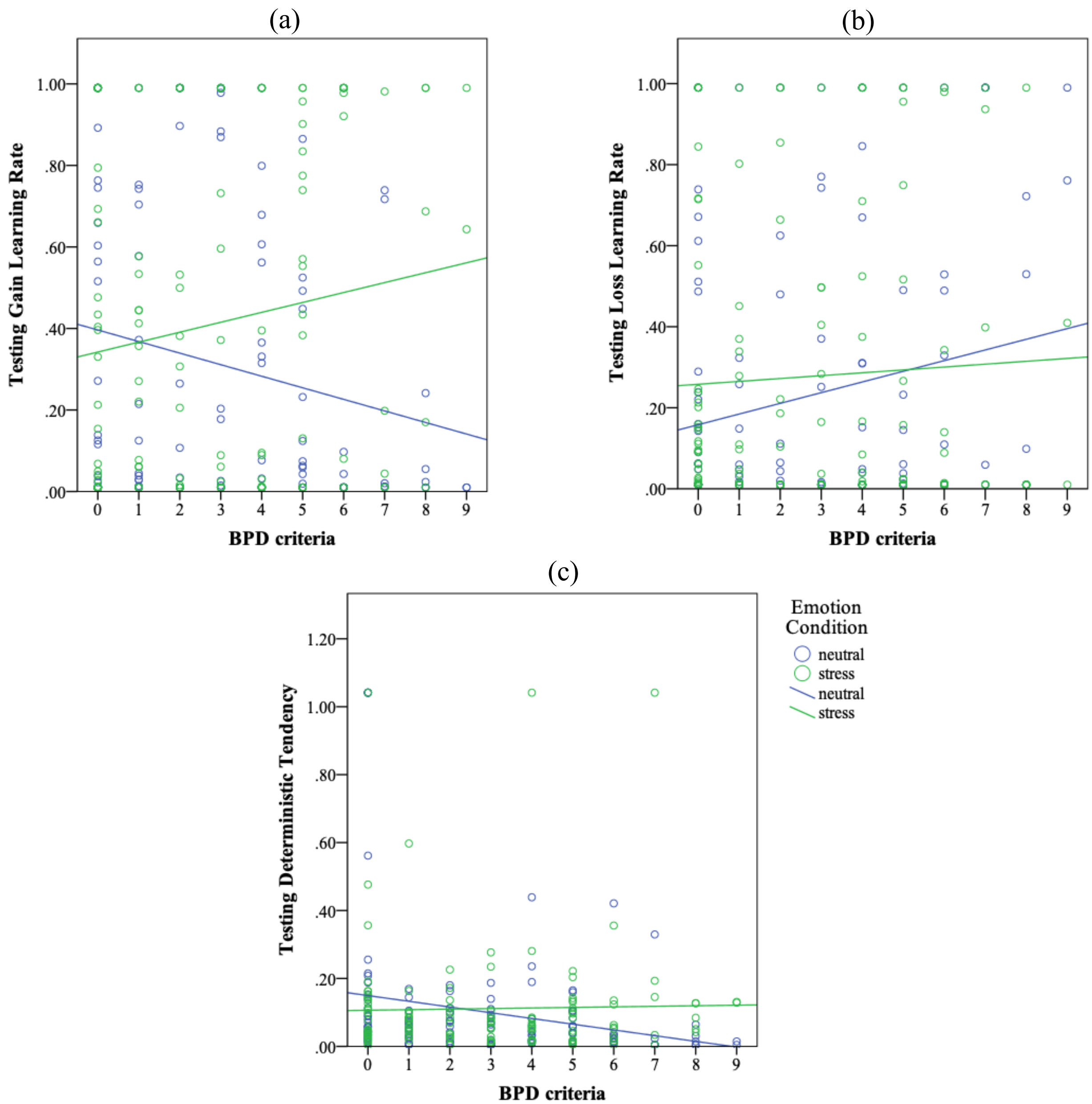
Scatterplots of Training Phase Learning Parameters by BPD Criteria and Emotion Condition



Note. (a) Gain learning rate during the training phase, (b) Loss learning rate during the training phase, and (c) Deterministic tendency during the training phase, log10 transformed.

Figure 4

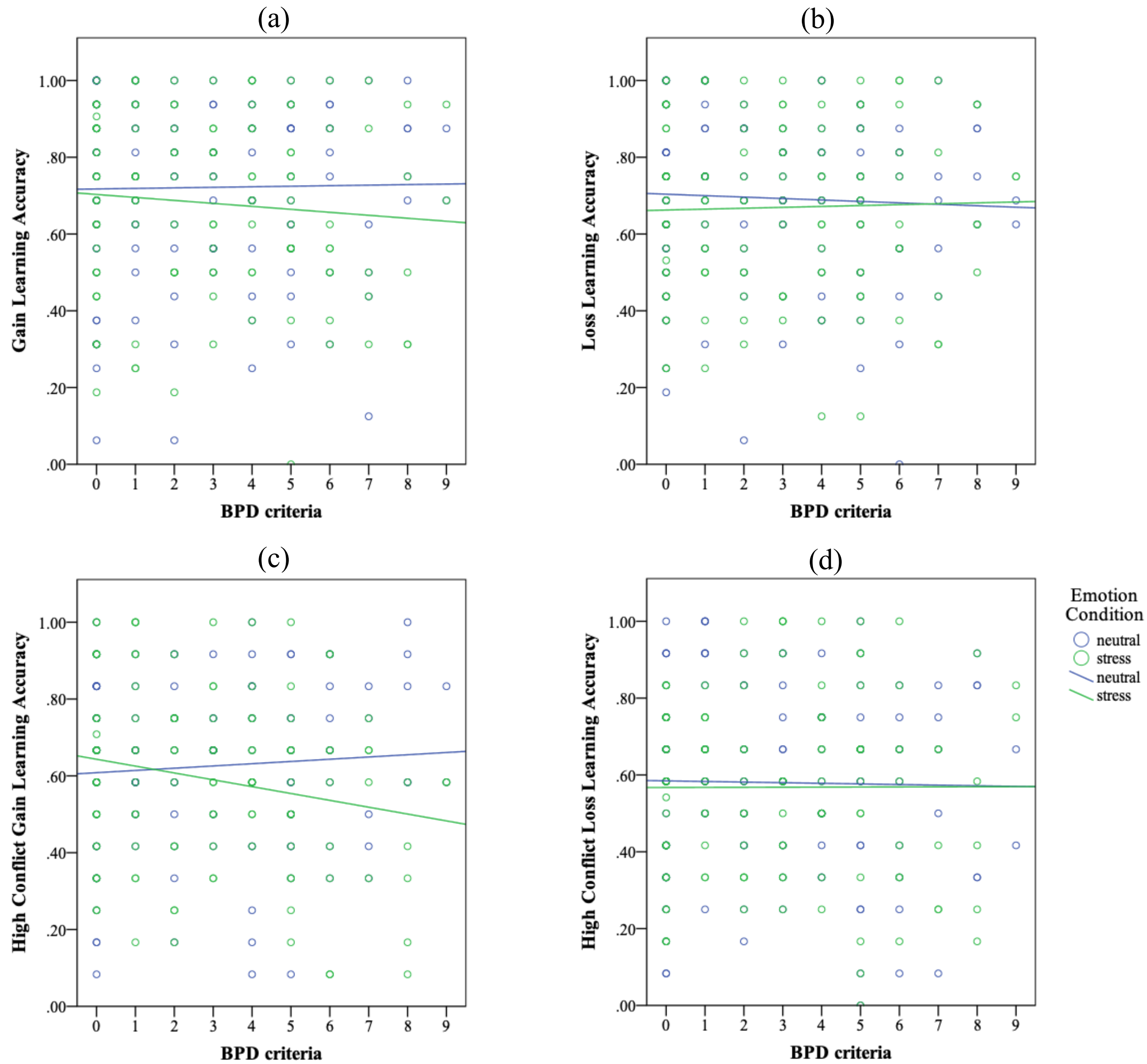
Scatterplots of Test Phase Learning Parameters by BPD Criteria and Emotion Condition



Note. (a) Gain learning rate during the test phase, (b) Loss learning rate during the test phase, and (c) Deterministic tendency during the test phase, log10 transformed.

Figure 5

Scatterplots of Learning Accuracy by BPD Criteria and Emotion Condition



Note. (a) Gain Learning Accuracy on all trials, (b) Loss Learning Accuracy on all trials, (c) Gain Learning Accuracy on High Conflict trials, and (d) Loss Learning Accuracy on High Conflict trials.

APPENDICES

Appendix A

DSM-5 Diagnostic Criteria for Borderline Personality Disorder (American Psychiatric Association, 2013)

"A pervasive pattern of instability of interpersonal relationships, self-image, and affects, and marked impulsivity, beginning by early adulthood and present in a variety of contexts, as indicated by five (or more) of the following:

1. Frantic efforts to avoid real or imagined abandonment
2. A pattern of unstable and intense interpersonal relationships characterized by alternating between extremes of idealization and devaluation
3. Identity disturbance: markedly and persistently unstable self-image or sense of self
4. Impulsivity in at least two areas that are potentially self-damaging
5. Recurrent suicidal behavior, gestures, or threats, or self-mutilating behavior
6. Affective instability due to a marked reactivity of mood
7. Chronic feelings of emptiness
8. Inappropriate, intense anger or difficulty controlling anger
9. Transient, stress-related paranoid ideation or sever dissociative symptoms"

Appendix B

Personality Assessment Inventory – Borderline Features Scale (Morey, 1991)

Instructions: This questionnaire consists of numbered statements. Read each statement and indicate the extent to which it is an accurate statement about you. Give your own opinion of yourself. Be sure to answer every statement.

	False, Not at All True	Slightly True	Mainly True	Very True
1. My mood can shift quite suddenly.	**0**	**1**	**2**	**3**
2. My attitude about myself changes a lot.	**0**	**1**	**2**	**3**
3. My relationships have been stormy.	**0**	**1**	**2**	**3**
4. My moods get quite intense.	**0**	**1**	**2**	**3**
5. Sometimes I feel terribly empty inside.	**0**	**1**	**2**	**3**
6. I want to let certain people know how much they've hurt me.	**0**	**1**	**2**	**3**
7. My mood is very steady.	**0**	**1**	**2**	**3**
8. I worry a lot about other people leaving me.	**0**	**1**	**2**	**3**
9. People once close to me have let me down.	**0**	**1**	**2**	**3**
10. I have little control over my anger.	**0**	**1**	**2**	**3**

	False, Not at All True	Slightly True	Mainly True	Very True
11. I often wonder what I should do with my life.	**0**	**1**	**2**	**3**
12. I rarely feel very lonely.	**0**	**1**	**2**	**3**
13. I sometimes do things so impulsively that I get into trouble.	**0**	**1**	**2**	**3**
14. I've always been a pretty happy person.	**0**	**1**	**2**	**3**
15. I can't handle separation from those close to me very well.	**0**	**1**	**2**	**3**
16. I've made some real mistakes in the people I've picked as friends.	**0**	**1**	**2**	**3**
17. When I'm upset, I typically do something to hurt myself.	**0**	**1**	**2**	**3**
18. I've had times when I was so mad I couldn't do enough to express all my anger.	**0**	**1**	**2**	**3**
19. I don't get bored very easily.	**0**	**1**	**2**	**3**
20. Once someone is my friend, we stay friends.	**0**	**1**	**2**	**3**
21. I'm too impulsive for my own good.	**0**	**1**	**2**	**3**

	False, Not at All True	Slightly True	Mainly True	Very True
22. I spend money too easily.	**0**	**1**	**2**	**3**
23. I'm a reckless person.	**0**	**1**	**2**	**3**
24. I'm careful about how I spend my money.	**0**	**1**	**2**	**3**

BIBLIOGRAPHY

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). American Psychiatric Publishing.

Aylward, J., Valton, V., Ahn, W.-Y., Bond, R. L., Dayan, P., Roiser, J. P., & Robinson, O. J. (2019). Altered learning under uncertainty in unmedicated mood and anxiety disorders. *Nature Human Behaviour*, *3*(10), 1116–1123. https://doi.org/10.1038/s41562-019-0628-0

Barker, V., Romaniuk, L., Cardinal, R. N., Pope, M., Nicol, K., & Hall, J. (2015). Impulsivity in borderline personality disorder. *Psychological Medicine*, *45*(9), 1955–1964. https://doi.org/10.1017/S0033291714003079

Bazanis, E., Rogers, R. D., Dowson, J. H., Taylor, P., Meux, C., Staley, C., Nevinson-Andrews, D., Taylor, C., Robbins, T. W., & Sahakian, B. J. (2002). Neurocognitive deficits in decision-making and planning of patients with DSM-III-R borderline personality disorder. *Psychological Medicine*, *32*(8), 1395–1405. https://doi.org/10.1017/S0033291702006657

Bolton, J. M., & Robinson, J. (2010). Population-attributable fractions of Axis I and Axis II mental disorders for suicide attempts: findings from a representative sample of the adult, noninstitutionalized US population. *American Journal of Public Health*, *100*(12), 2473–2480. https://doi.org/10.2105/AJPH.2010.192252

Cavanagh, J. F., Frank, M. J., & Allen, J. J. B. (2011). Social stress reactivity alters reward and punishment learning. *Social Cognitive and Affective Neuroscience*, *6*(3), 311–320. https://doi.org/10.1093/scan/nsq041

Cavanagh, J. F., Frank, M. J., Klein, T. J., & Allen, J. J. B. (2010). Frontal theta links prediction errors to behavioral adaptation in reinforcement learning. *NeuroImage*, *49*(4), 3198–3209. https://doi.org/10.1016/J.NEUROIMAGE.2009.11.080

Chapman, A. L., Dixon-Gordon, K. L., Layden, B. K., & Walters, K. N. (2010). Borderline personality features moderate the effect of a fear induction on impulsivity. *Personality Disorders: Theory, Research, and Treatment*, *1*(3), 139–152. https://doi.org/10.1037/a0019226

Chapman, A. L., Leung, D. W., & Lynch, T. R. (2008). Impulsivity and emotion dysregulation in borderline personality disorder. *Journal of Personality Disorders*, *22*(2), 148–164. https://doi.org/10.1017/CBO9781139042734.035

Chapman, A. L., Rosenthal, M. Z., & Leung, D. W. (2009). Emotion suppression in borderline personality disorder: An experience sampling study. *Journal of Personality Disorders*, *23*(1), 29–47. https://doi.org/10.1521/pedi.2009.23.1.29

Chase, H. W., Frank, M. J., Michael, A., Bullmore, E. T., Sahakian, B. J., & Robbins, T. W. (2010). Approach and avoidance learning in patients with major depression and healthy controls: relation to anhedonia. *Psychological Medicine*, *40*, 433–440. https://doi.org/10.1017/S0033291709990468

Chen, C., Takahashi, T., Nakagawa, S., Inoue, T., & Kusumi, I. (2015). Reinforcement learning in depression: A review of computational research. *Neuroscience & Biobehavioral Reviews*, *55*, 247–267. https://doi.org/10.1016/j.neubiorev.2015.05.005

Coffey, S. F., Schumacher, J. A., Baschnagel, J. S., Hawk, L. W., & Holloman, G. (2011). Impulsivity and risk-taking in borderline personality disorder with and without substance use disorders. *Personality Disorders: Theory, Research, and*

Treatment, *2*(2), 128–141. https://doi.org/10.1037/a0020574

Culver, N. C., Vervliet, B., & Craske, M. G. (2015). Compound Extinction: Using the Rescorla–Wagner Model to Maximize Exposure Therapy Effects for Anxiety Disorders. *Clinical Psychological Science*, *3*(3), 335–348. https://doi.org/10.1177/2167702614542103

De Panfilis, C., Schito, G., Generali, I., Gozzi, L. A., Ossola, P., Marchesi, C., & Grecucci, A. (2019). Emotions at the border: Increased punishment behavior during fair interpersonal exchanges in borderline personality disorder. *Journal of Abnormal Psychology*, *128*(2), 162–172. https://doi.org/10.1037/abn0000404

Dixon-Gordon, K. L., Chapman, A. L., Lovasz, N., & Walters, K. N. (2011). Too upset to think: The interplay of borderline personality features, negative emotions, and social problem solving in the laboratory. *Personality Disorders: Theory, Research, and Treatment*, *2*(4), 243–260. https://doi.org/10.1037/a0021799

Dixon-Gordon, K. L., Hackel, L. M., Tull, M. T., & Gratz, K. L. (2018). The influence of emotional state on reinforcement learning in borderline personality disorder. *Journal of Personality Disorders*, *32*(4), 433–446. https://doi.org/10.1521/pedi_2017_31_299

Dombrovski, A. Y., Clark, L., Siegle, G. J., Butters, M. A., Ichikawa, N., Sahakian, B. J., & Szanto, K. (2010). Reward/punishment reversal learning in older suicide attempters. *American Journal of Psychiatry*, *167*(6), 699–707. https://doi.org/10.1176/appi.ajp.2009.09030407

Dyck, M., Habel, U., Slodczyk, J., Schlummer, J., Backes, V., Schneider, F., & Reske, M. (2008). Negative bias in fast emotion discrimination in borderline personality

disorder. *Psychological Medicine*, *39*(5).
https://doi.org/10.1017/S0033291708004273

Endrass, T., Schuermann, B., Roepke, S., Kessler-Scheil, S., & Kathmann, N. (2016). Reduced risk avoidance and altered neural correlates of feedback processing in patients with borderline personality disorder. *Psychiatry Research*, *243*, 14–22. https://doi.org/10.1016/j.psychres.2016.06.016

Endres, M. J., Rickert, M. E., Bogg, T., Lucas, J., & Finn, P. R. (2012). Externalizing psychopathology and behavioral disinhibition: Working memory mediates signal discriminability and reinforcement moderates response bias in approach-avoidance learning. *Journal of Abnormal Psychology*, *120*(2), 336–351. https://doi.org/10.1037/a0022501.Externalizing

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Ferreira, G. C. S., Sanches, R. F., Alexandre De Souza Crippa, J., Feijó De Mello, M., & Osório, F. L. (2018). Borderline personality disorder and bias in the recognition of facial expressions of emotion: a pathway to understand the psychopathology. *Archives of Clinical Psychiatry*, *45*(1), 7–11. https://doi.org/10.1590/0101-60830000000146

Fineberg, S. K., Hu, J., Null, K. E., Neustadter, E. S., Sakheim, M. E., & Corlett, P. R. (2019). Associative learning profiles in borderline personality disorder: Acquisition, Kamin blocking, and metacognitive performance. *Psych Archives Pre Prints*.

Fineberg, S. K., Leavitt, J., Stahl, D. S., Kronemer, S., Landry, C. D., Alexander-Bloch, A., Hunt, L. T., & Corlett, P. R. (2018). Differential Valuation and Learning From Social and Nonsocial Cues in Borderline Personality Disorder. *Biological Psychiatry*, *84*(11), 838–845. https://doi.org/10.1016/j.biopsych.2018.05.020

Fineberg, S. K., Steinfeld, M., Brewer, J. A., & Corlett, P. R. (2014). A computational account of borderline personality disorder: Impaired predictive learning about self and others through bodily simulation. *Frontiers in Psychiatry*, *5*(AUG), 1–7. https://doi.org/10.3389/fpsyt.2014.00111

First, M. B., Williams, J. B., Karg, R. S., & Spitzer, R. L. (2015). *Structured Clinical Interview for DSM-5 Disorders Clinical Trials Version (SCID-5-CT)*. American Psychiatric Publishing.

Frank, M. J., Moustafa, A. A., Haughey, H. M., Curran, T., & Hutchison, K. E. (2007). Genetic triple dissociation reveals multiple roles for dopamine in reinforcement learning. *Proceedings of the National Academy of Sciences*, *104*(41), 16311–16316. www.pnas.org/cgi/content/full/

Frank, M. J., Woroch, B. S., & Curran, T. (2005). Error-related negativity predicts reinforcement learning and conflict biases. *Neuron*, *47*(4), 495–501. https://doi.org/10.1016/j.neuron.2005.06.020

Gagne, C., Zika, O., Dayan, P., & Bishop, S. J. (2020). Impaired adaptation of learning to contingency volatility in internalizing psychopathology. *ELife*, *9*. https://doi.org/10.7554/eLife.61387

Gratz, K. L., Bardeen, J. R., Levy, R., Dixon-Gordon, K. L., & Tull, M. T. (2015). Mechanisms of change in an emotion regulation group therapy for deliberate self-harm among women with borderline personality disorder. *Behaviour Research and Therapy*, *65*, 29–35. https://doi.org/10.1016/j.brat.2014.12.005

Gratz, K. L., Hepworth, C., Tull, M. T., Paulson, A., Clarke, S., Remington, B., & Lejuez, C. W. (2011). An experimental investigation of emotional willingness and physical pain tolerance in deliberate self-harm: The moderating role of interpersonal distress. *Comprehensive Psychiatry*, *52*(1), 63–74. https://doi.org/10.1016/j.comppsych.2010.04.009

Gunderson, J. G., Herpertz, S. C., Skodol, A. E., Torgersen, S., & Zanarini, M. C. (2018). Borderline personality disorder. *Nature Reviews Disease Primers*, *4*, 18029. https://doi.org/10.1038/nrdp.2018.29

Haaland, V. Ø., & Landrø, N. I. (2007). Decision making as measured with the Iowa Gambling Task in patients with borderline personality disorder. *Journal of the International Neuropsychological Society*, *13*, 699–703. https://doi.org/10.1017/S1355617707070890

Hackel, L. M., Doll, B. B., & Amodio, D. M. (2015). Instrumental learning of traits versus rewards: Dissociable neural correlates and effects on choice. *Nature Neuroscience*, *18*(9), 1233–1235. https://doi.org/10.1038/nn.4080

Hamza, C. A., Willoughby, T., & Heffer, T. (2015). Impulsivity and nonsuicidal self-injury: A review and meta-analysis. *Clinical Psychology Review*, *38*, 13–24. https://doi.org/10.1016/j.cpr.2015.02.010

Hebb, D. O. (1949). *The Organization of Behaviour*. John Wiley & Sons, Inc. https://doi.org/citeulike-article-id:1282862

Hill, J., Pilkonis, P., Morse, J., Feske, U., Reynolds, S., Hope, H., Charest, C., &

Broyden, N. (2008). Social domain dysfunction and disorganization in borderline personality disorder. *Psychological Medicine*, *38*, 135–146. https://doi.org/10.1017/S0033291707001626

Holroyd, C. B., & Coles, M. G. H. (2002). The neural basis of human error processing: Reinforcement learning, dopamine, and the error-related negativity. *Psychological Review*, *109*(4), 679–709. https://doi.org/10.1037/0033-295X.109.4.679

Huys, Q. J., Pizzagalli, D. A., Bogdan, R., & Dayan, P. (2013). Mapping anhedonia onto reinforcement learning: a behavioural meta-analysis. *Biology of Mood & Anxiety Disorders*, *3*(1), 12. https://doi.org/10.1186/2045-5380-3-12

Jennings, J. R., Kamarck, T., Stewart, C., Eddy, M., & Johnson, P. (1992). Alternate cardiovascular baseline assessment techniques: Vanilla or resting baseline. *Psychophysiology*, *29*(6), 742–750.

Kirkpatrick, T., Joyce, E., Milton, J., Duggan, C., Tyrer, P., & Rogers, R. D. (2007). Altered emotional decision-making in prisoners with borderline personality disorder. *Journal of Personality Disorders*, *21*(3), 243–261. https://doi.org/10.1521/pedi.2007.21.3.243

Kunisato, Y., Okamoto, Y., Ueda, K., Onoda, K., Yoshimura, S., Suzuki, S.-I., Samejima, K., & Yamawaki, S. (2012). Effects of depression on reward-based decision making and variability of action in probabilistic learning. *Journal of Behavior Therapy and Expereimental Psychology*, *43*, 1088–1094. https://doi.org/10.1016/j.jbtep.2012.05.007

Lawrence, K. A., Allen, J. S., & Chanen, A. M. (2010). Impulsivity in Borderline Personality Disorder: Reward-Based Decision-Making and its Relationship to

Emotional Distress. *Journal of Personality Disorders*, *24*(6), 785–799. https://doi.org/10.1521/pedi.2010.24.6.785

LeGris, J., Toplak, M., & Links, P. S. (2014). Affective decision making in women with borderline personality disorder. *Journal of Personality Disorders*, *28*(5), 1–22. https://doi.org/10.1521/pedi_2014_28_140

Linehan, M. M. (1993). *Cognitive–behavioral treatment of borderline personality disorder*. Guilford Press.

Lis, S., & Bohus, M. (2013). Social Interaction in Borderline Personality Disorder. *Current Psychiatry Reports*, *15*(2), 338. https://doi.org/10.1007/s11920-012-0338-z

Lynch, T. R., Rosenthal, M. Z., Kosson, D. S., Cheavens, J. S., Lejuez, C. W., & Blair, R. J. R. (2006). Heightened Sensitivity to Facial Expressions of Emotion in Borderline Personality Disorder. *Emotion*, *6*(4), 647–655. https://doi.org/10.1037/1528-3542.6.4.647

Maia, T. V., & Frank, M. J. (2011). From reinforcement learning models to psychiatric and neurological disorders. *Nature Neuroscience*, *14*(2), 154–162. https://doi.org/10.1038/nn.2723

Maurex, L., Zaboli, G., Wiens, S., Åsberg, M., Leopardi, R., & Öhman, A. (2009). Emotionally controlled decision-making and a gene variant related to serotonin synthesis in women with borderline personality disorder: Cognition and Neurosciences. *Scandinavian Journal of Psychology*, *50*(1), 5–10. https://doi.org/10.1016/j.tws.2017.01.029

Meaney, R., Hasking, P., & Reupert, A. (2016). Prevalence of borderline personality disorder in university samples: Systematic review, meta-analysis and metaregression. *PLoS ONE*, *11*(5), 1–15. https://doi.org/10.1371/journal.pone.0155439

Miller, G. A., & Chapman, J. P. (2001). Misunderstanding analysis of covariance. *Journal of Abnormal Psychology*, *110*(1), 40–48. https://doi.org/10.1037//0021-843x.110.1.40

Morey, L. C. (1991). *Personality assessment inventory: Professional manuel*. Psychological Assessment Resources.

Muthén, L. K., & Muthén, B. O. (2018). *Mplus* (8.1). Muthén & Muthén.

Paret, C., Hoesterey, S., Kleindienst, N., & Schmahl, C. G. (2016). Associations of emotional arousal, dissociation and symptom severity with operant conditioning in borderline personality disorder. *Psychiatry Research*, *244,* 194–201.

Paret, C., Jennen-Steinmetz, C., & Schmahl, C. (2017). Disadvantageous decision-making in borderline personality disorder: Partial support from a meta-analytic review. *Neuroscience and Biobehavioral Reviews*, *72,* 301–309. https://doi.org/10.1016/j.neubiorev.2016.11.019

Pizzagalli, D. A., Iosifescub, D., Hallett, L. A., Ratnera, K. G., & Fava, M. (2009). Reduced hedonic capacity in major depressive disorder: Evidence from a probabilistic reward task. *Journal of Psychiatric Research*, *43*(1), 76–87. https://doi.org/10.1016/j.jpsychires.2008.03.001.Reduced

Reynolds, S. K., Lindenboim, N., Comtois, K. A., Murray, A., & Linehan, M. M. (2006). Risky assessments: Participant suicidality and distress associated with research assessments in a treatment study of suicidal behavior. *Suicide & Life-Threatening Behavior, 36*(1), 19–34.

Rock, P. L., Roiser, J. P., Riedel, W. J., & Blackwell, A. D. (2013). *Cognitive impairment* *in depression: a systematic review and meta-analysis*. https://doi.org/10.1017/S0033291713002535

Rönnlund, M., Nyberg, L., Bäckman, L., & Nilsson, L. G. (2005). Stability, growth, and decline in adult life span development of declarative memory: Cross-sectional and longitudinal data from a population-based study. *Psychology and Aging*, *20*(1), 3–18. https://doi.org/10.1037/0882-7974.20.1.3

Rothkirch, M., Tonn, J., Köhler, S., & Sterzer, P. (2017). Neural mechanisms of reinforcement learning in unmedicated patients with major depressive disorder. *Brain*, *140*(4), 1147–1157. https://doi.org/10.1093/brain/awx025

Sánchez-Navarro, J. P., Weller, J. A., López-Navarro, J. M., Martínez-Selva, J. M., & Bechara, A. (2014). Suboptimal decision making in borderline personality disorder: Effect of potential losses. *The Spanish Journal of Psychology*, *17*(2014), E38. https://doi.org/10.1017/sjp.2014.39

Scholl, J., & Klein-Flügge, M. (2018). Understanding psychiatric disorder by capturing ecologically relevant features of learning and decision-making. *Behavioural Brain Research*, *355*(July 2017), 56–75. https://doi.org/10.1016/j.bbr.2017.09.050

Schuermann, B., Kathmann, N., Stiglmayr, C., Renneberg, B., & Endrass, T. (2011). Impaired decision making and feedback evaluation in borderline personality disorder. *Psychological Medicine*, *41*(9), 1917–1927. https://doi.org/10.1017/S003329171000262X

Segers, E., Beckers, T., Geurts, H., Claes, L., Danckaerts, M., & van der Oord, S. (2018). Working Memory and Reinforcement Schedule Jointly Determine Reinforcement Learning in Children: Potential Implications for Behavioral Parent Training.

Frontiers in Psychology, *9*, 394. https://doi.org/10.3389/fpsyg.2018.00394

Sheehan, D., Lecrubier, Y., Sheehan, K., Amorim, P., Janavs, J., Weiller, E., Hergueta, T., Baker, R., & Dunbar, G. (1998). The Mini-International Neuropsychiatric Interview (MINI): The development and validation of a structured diagnostic psychiatric interview for DSM-IV and ICD-10. *Journal of Clinical Psychiatry*, *59*, 22–33.

Skodol, A. E., Pagano, M. E., Bender, D. S., Shea, M. T., Gunderson, J. G., Yen, S., Stout, R. L., Morey, L. C., Sanislow, C. A., Grilo, C. M., Zanarini, M. C., & Mcglashan, T. H. (2005). Stability of functional impairment in patients with schizotypal, borderline, avoidant, or obsessive-compulsive personality disorder over two years. *American Journal of Psychiatry*, *159*, 276–283. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3272760/pdf/nihms349852.pdf

Stepp, S. D., Scott, L. N., Jones, N. P., Whalen, D. J., & Hipwell, A. E. (2016). Negative emotional reactivity as a marker of vulnerability in the development of borderline personality disorder symptoms. *Development and Psychopathology*, *28*(1), 213–224. https://doi.org/10.1017/S0954579415000395

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement Learning: An Introduction* (2nd ed.). The MIT Press.

Svaldi, J., Philipsen, A., & Matthies, S. (2012). Risky decision-making in borderline personality disorder. *Psychiatry Research*, *197*(1–2), 112–118. https://doi.org/10.1016/j.psychres.2012.01.014

Tottenham, N., Tanaka, J. W., Leon, A. C., McCarry, T., Nurse, M., Hare, T. A., Marcus, D. J., Westerlund, A., Casey, B. J., & Nelson, C. (2009). The NimStim set of facial expressions: Judgments from untrained research participants. *Psychiatry Research*, *168*(3), 242–249. https://doi.org/10.1016/j.psychres.2008.05.006

Trull, T. J. (1995). Borderline personality disorder features in nonclinical young adults: 1. Identification and validation. *Psychological Assessment*, *7*(1), 33–41. https://www.researchgate.net/profile/Timothy_Trull/publication/232443604_Comparison_of_the_MMPI-2_personality_psychopathology_five_PSY-5_the_NEO-PI_and_the_NEO-PI-R/links/0deec52af2f0b93ce3000000/Comparison-of-the-MMPI-2-personality-psychopathology-five-P

Trull, T. J., Distel, M. a, & Carpenter, R. W. (2011). DSM-5 Borderline personality disorder: At the border between a dimensional and a categorical view. *Current Psychiatry Reports*, *13*(1), 43–49. https://doi.org/10.1007/s11920-010-0170-2

Tsypes, A., Owens, M., & Gibb, B. E. (2020). Reward responsiveness in suicide attempters: An electroencephalography/event-related potential study. *Biological Psychiatry,* epub before print. https://doi.org/10.1016/j.bpsc.2020.04.003 PMCID: PMC7581535

Tull, M. T., Gratz, K. L., & Weiss, N. H. (2011). Exploring associations between borderline personality disorder, crack/cocaine dependence, gender, and risky sexual behavior among substance-dependent inpatients. *Personality Disorders: Theory, Research, and Treatment*, *2*(3), 209–219. https://doi.org/10.1037/a0021878

Unoka, Z., Fogd, D., Füzy, M., & Csukly, G. (2011). Misreading the facial signs: Specific impairments and error patterns in recognition of facial emotions with negative valence in borderline personality disorder. *Psychiatry Research, 189*, 419–425. https://doi.org/10.1016/j.psychres.2011.02.010

van Asselt, A. D. I., Dirksen, C. D., Arntz, A., & Severens, J. L. (2007). The cost of borderline personality disorder: societal cost of illness in BPD-patients. *European Psychiatry*, *22*(6), 354–361. https://doi.org/10.1016/j.eurpsy.2007.04.001

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, *54*(6), 1063–1070. https://doi.org/10.1037/0022-3514.54.6.1063

Whitmer, A. J., Frank, M. J., & Gotlib, I. H. (2012). Sensitivity to reward and punishment in major depressive disorder: Effects of rumination and of single versus multiple experiences. *Cognition and Emotion*, *26*(8), 1475–1485. https://doi.org/10.1080/02699931.2012.682973

Wiehler, A., Chakroun, K., & Peters, J. (2021). Behavioral/Cognitive Attenuated Directed Exploration during Reinforcement Learning in Gambling Disorder. *The Journal of Neuroscience*, *41*(11), 2512–2522. https://doi.org/10.1523/JNEUROSCI.1607-20.2021

Zanarini, M. C., Frankenburg, F. R., Hennen, J., Reich, D. B., & Silk, K. R. (2004). Axis I comorbidity in patients with borderline personality disorder: 6-year follow-up and prediction of time to remission. *American Journal of Psychiatry*, *161*, 2108–2114. https://doi.org/10.1176/appi.ajp.161.11.2108