Decision Making Under Chronic Stress and Anxiety: State and Trait Anxiety Impact Updating Working Memory but not Feedback Learning

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Abstract

Stress may alter executive functioning by causing structural and functional changes to the brain. Sub-optimal decisions made under high levels of stress and anxiety may act as a mediator for stress-related health effects. We examined the effect of three personality traits–chronic stress, state anxiety, and trait anxiety–on updating working memory and feedback learning across 330 participants, using electroencephalography (EEG). We hypothesized a decrease in P300 (updating working memory) and reward positivity (feedback learning) amplitudes with increasing chronic stress and anxiety scores. The three personality traits were not correlated with reward positivity amplitudes. Additionally, chronic stress had no effect on P300 amplitudes. However, state and trait anxiety were negatively correlated with P300 amplitudes. Anxiety appears to impact working memory processes, and this effect was amplified with decreasing anxiety score quantiles to reflect the tails of the distribution. Our results are evidence of the beginnings of a correlation between anxiety and the neural correlates of decision-making, offering insight into anxiety-related adverse health outcomes.

Keywords: chronic stress; anxiety; decision-making; EEG; ERPs

[1] Juliet Rowe would like to acknowledge support from a Jamie Cassels Undergraduate Research Award, and all authors would like to acknowledge the support from the Natural Sciences and Engineering Research Council of Canada (RGPIN 2016-0943).

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Humans are frequently required to make decisions under stress. For example, during a global pandemic, stress levels increase (Park et al., 2020) as the government mandates social distancing protocols, quarantines, and lockdowns. Generally, stress can be defined as a threat to well-being (Herman, 2013; Lupien et al., 2007). These threats can be physical (unemployment) or mental (feeling, attitudes) and they disrupt homeostasis by altering our physiological, psychological, and emotional states (Lupien et al., 2007). Additionally, stress can be divided into acute stress and chronic stress. Acute stress is our short-term response to stress, whereas chronic stress is a form of stress that occurs when our perception of a threat persists for a longer period of time (Eggers, 2007). Stress can drive individuals to seek immediate reward, with little concern for long-term consequences (Starcke & Brand, 2012). In fact, structural and functional changes to the brain that alter executive functioning may occur as a result of stress (McEwen & Morrison, 2013). Consequently, suboptimal decision-making may act as a mediator for health-related stress effects (Starcke & Brand, 2012). In the present work, we sought to determine the correlations between personality measures such as chronic stress and anxiety and common cognitive abilities implicated in decision making.

Chronic stress has profound impacts on our health and well-being. Many detrimental health effects are linked to chronic stress: increased risk for psychosomatic, psychiatric, and cardiovascular diseases (Jeong et al., 2006; Rakshasa & Tong, 2020); increased risk for tumor growth (Rakshasa & Tong, 2020; Thaker et al., 2006); and acceleration of memory impairments (Jeong et al., 2006; Rakshasa & Tong, 2020). Structural and functional alterations to the prefrontal cortex (PFC) have been observed in chronically stressed rats, indicating altered executive function (Dias-Ferreira et al., 2009; Rakshasa & Tong, 2020). Chronically stressed rats also displayed reduced PFC dopamine transmission (Mizoguchi et al., 2000), impaired working memory (Mika et al, 2012; Mizoguchi et al., 2000), and impaired response inhibition (Mika et al., 2012). These animal studies provide evidence for chronic stress effects on executive function; however, manipulating chronic stress in humans is difficult (i.e., ethics approval is near impossible). Rather, human studies must rely on surveys and behavioural tests–for example, chronic stress can be measured using the Trier Inventory for Chronic Stress (TICS) survey (Schulz et al., 2004). Human studies on chronic stress have observed decreased working memory capacity (Evans & Fuller-Rowell, 2013), and impaired working memory performance (Korten et al., 2014). However, more research on the effects of chronic stress on human decision making are needed for a better understanding as these human studies lack concrete electrophysiological data and large diverse populations.

Anxiety, an emotion that individuals feel when the future is interpreted to contain dangers (Craske & Stein, 2016), is closely associated with the stress response. For example, during the pandemic, someone might feel anxious due to uncertainties about safety, long-term health effects, and resuming normal life. Stress and emotion are interdependent: a stressful event can induce a heightened emotional response (however, not all emotions are related to stress). Pertinently, as someone becomes more stressed out, their anxiety levels rise (Lazarus, 2006). Animal studies have linked anxiety to altered executive functioning, whereby anxious rats showed structural and functional changes to the PFC (Fragale et al., 2016; Park et al., 2016). Similar to chronic stress

research, human studies rely heavily on surveys and behavioural tests–typically, anxiety is measured using the State-Trait Anxiety Inventory (STAI; Spielberger, 2010). In human anxiety research, anxiety is usually conceptualized into two components: state anxiety and trait anxiety. State anxiety evaluates current anxiety states (tension, worry, nervousness), whereas trait anxiety evaluates anxiety proneness (security, confidence, calmness; Spielberger & Reheiser, 2009). State anxiety affects a human's executive functioning by impairing cognitive control (Yang et al., 2018) and attentional control (Derakshan et al., 2009). Trait anxiety impairs decision making during uncertainty (making decisions without knowing the outcome; Zhang et al., 2015) and emotional decision making (Xu et al., 2013).

Electroencephalography (EEG) is a neuroimaging technique that can be used to further investigate chronic stress and anxiety by exploring their effects on more specific aspects of decision making. Specifically, this is done by examining event-related potentials (ERPs). ERPs make up features of EEG waveforms that are related to the activity of specific neuronal populations that are thought to represent certain psychological processes (Luck, 2014). For example, EEG allows for the investigation of working memory (P300[2] ERP component) and feedback learning (reward positivity[3] ERP component). On one hand, the most current theory[4] of the P300 functionality is updating working memory (Luck, 2014; Polich, 2007; San Martin, 2012). As the brain processes incoming information, an evaluation between previous events and incoming events takes place in working memory. The P300 is elicited during the oddball task and provides valuable information about the process of working memory: the amplitude represents memory load (Wang et al., 2015) and it changes based on stimulus frequency and task effort (Luck, 2014), while the latency of the P300 represents speed of classification and is proportional to the time for detection and evaluation (Polich, 2007). On the other hand, reward-related neural activity is indexed by reward positivity (Proudfit, 2015), and its functionality is theorized to provide the neural basis for feedback learning (Holroyd et al., 2011; Proudfit, 2015; San Martin, 2012; Yaple et al., 2018). Feedback learning uses either positive or negative feedback to compute a prediction error, integrating the difference between expected outcome and actual outcome. Reward positivity is the difference between the neural response to the positive and negative/neutral feedback. Reward positivity is elicited during the gambling task and provides valuable information about the process of feedback learning: The amplitude of the reward positivity difference waveform is theorized to represent the degree of unpredictability for reward-related events (Holroyd et al., 2011). Reward prediction error theory suggests that the size of the elicited reward positivity difference waves is directly correlated with events that are unpredicted. In other words, unexpected outcomes elicit larger reward positivity responses than expected outcomes (Holroyd et al., 2011).

ERP research on chronic stress has explored a narrow range of topics in regard to decision making. It is suggested that chronic stress was associated with (1) weakened recognition memory and heightened attentional processing (Wirkner et al., 2019), and (2) reduced cortical anticipatory activity (Shi & Wu, 2020) as indicated by changes to late positive potentials (LPPs) and early contingent negative variations (CNVs), respectively. Additionally, chronically stressed individuals

[2] Also referred to as P3 or P3b (Luck, 2014)

[3] Reward positivity is sometimes referred to as feedback related negativity. These ERP components represent the same construct: feedback learning (Holroyd et al., 2011; Polich, 2015). For the purpose of this paper, we will use solely reward positivity.

[4] Research has yet to identify one concrete definition of the cognitive processes that the P300 wave reflects. As of right now, this is just a theory.

appeared to have altered initiation of working memory processing as indicated by increased P2 amplitudes (Yuan et al., 2016). However, chronic stress ERP research has yet to investigate changes to the P300 ERP component. As for feedback learning, the focus of ERP studies has been on acute stress, and no studies have examined the impacts of chronic stress on reward positivity. Acute stress impairs feedback learning as evidenced by altered reward positivity waveforms, beta power, and theta power in stressed groups when compared to non-stress groups (Banis et al., 2014; Paul et al., 2016). Thus, while acute stress appears to alter feedback learning, no research currently exists on the impact of chronic stress on feedback learning.

Currently, ERP research has focussed more on the effects of trait anxiety on decision making impairments as opposed to the effects of state anxiety. Existing ERP research on decision making under state anxiety suggests that high state anxiety was associated with (1) appraising stimuli as threatening (Luo et al., 2018; Pederson & Larson, 2016) and (2) increasing cortical anticipatory activity (Duan et al., 2015), as indicated by changes to LPPs and CNVs. Individuals with high state anxiety tend towards longer P300 latencies (Ignatova et al., 2018) and reduced P300 amplitudes (Rossi & Pourtois, 2017). Currently no literature has explored the effect of state anxiety on feedback learning. On the other hand, research on using ERPs to investigate decision making impairments under trait anxiety has explored updating working memory and feedback learning. Individuals with high trait anxiety were more susceptible to impulsive decisions as indicated by increased P300 amplitudes for immediate decisions and dampened amplitudes for delayed decisions (Xia et al., 2017). Additionally, individuals with high trait anxiety also biased attention towards negative stimuli, prolonging P300 latencies (Wang et al., 2013), and decreasing P300 amplitudes (Huang et al., 2009). Changes to the reward positivity waveform suggests that individuals with high trait anxiety overestimated the value of reward for immediate choices (Xia et al., 2017; Zhang et al., 2018) and negatively evaluated ambiguous information (Gu et al., 2010). Researchers note changes to the P300 and reward positivity waveforms as a result of high trait anxiety, but the strength of these relationships has not been established. Thus, further investigation across diverse populations is needed across both state and trait anxiety to solidify the impact that these personality measures have on decision making processes including updating working memory and feedback learning.

The current literature on chronic stress, state anxiety, and trait anxiety fails to address critical components of decision making–updating working memory and feedback learning–and fails to explore the strength of these relationships. The National Institute of Mental Health (NIMH) has estimated that 31.1% of American adults will be affected by anxiety sometime in their lifetime (NIMH, n.d., "Prevalence of any anxiety disorder among adults," para. 4). Observing how these personality measures affect the neural correlates of decision-making aids in our understanding of the issues that can arise from stress and anxiety, such as stress-related adverse health conditions including psychosomatic, psychiatric, and cardiovascular diseases (Jeong et al., 2006; Rakshasa & Tong, 2020). The purpose of this large-scale observational ERP study was two-fold: (1) to assess correlations between chronic stress, state anxiety, and trait anxiety and (2) to assess the correlations between these personality measures and updating working memory and feedback learning. We hypothesized that as chronic stress, state anxiety, and trait anxiety increases–as measured by increases in negative affect scores on the TICS (chronic stress) and STAI (anxiety) surveys–the P300 and reward positivity amplitudes will decrease.

Methods

Participants

Participants consisted of 329 (215 Females, 114 Males) undergraduate university students (M age = 21.34, 95% CI = [20.87, 21.81]) and were recruited from the SONA research pool at the University of Victoria whereby students received extra credit in an undergraduate psychology course for their participation in the experiment. All participants had corrected-to-normal vision with no known neurological impairments and provided written informed consent prior to participation. Exclusion criteria included participants with neuropsychological disease or chronic illness, as well as individuals taking medications. Ethics were approved by the Human Research Ethics Board at the University of Victoria following the ethical standards that are outlined in the 1964 declaration of Helsinki.

Apparatus

Personality measurements

The Trier Inventory for Chronic Stress, long version, English (TICS-LE; Schulz et al., 2004) was used as a measurement of chronic stress. Participants answered the standard 57-item questionnaire, selecting from a 5-point scale of *never* to *very often*. Higher scores on select TICS-LE items–the Chronic Stress Screening Scale including items 09, 16, 18, 25, 31, 35, 36, 38, 44, 47, 54, 57–indicated higher levels of chronic stress.

The STAI (Spielberger, 2010) was used as a measurement of current states of anxiety (state anxiety) and anxiety proneness (trait anxiety). Participants answered two standard 20-item questionnaires (state and trait anxiety), selecting from a 4-point scale of *not at all* to *very much so*. Higher negative affects scores indicated higher levels of anxiety.

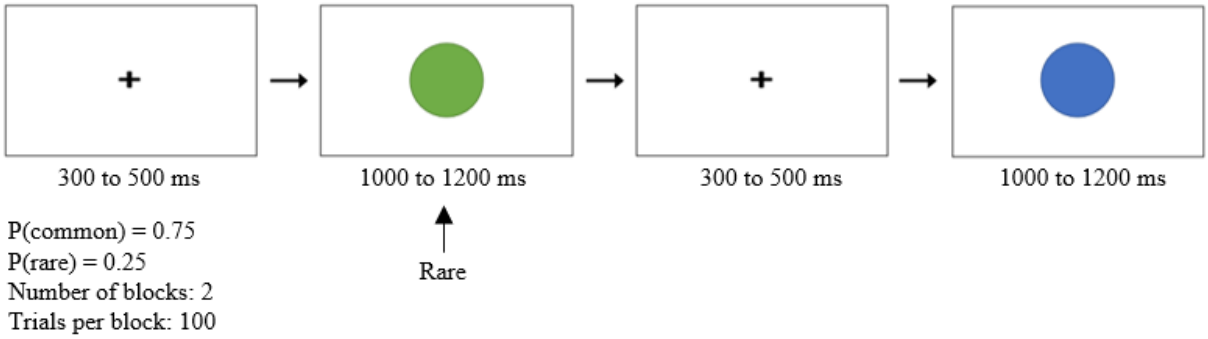
Cognitive Assessment

Four tasks were included in the cognitive assessment: The first task was focussing on a cross at the centre of the screen for a 30-second period; the second task was focussing on a cross at the centre of the screen while counting backwards from 1000 in steps of 7; the third and fourth task included an oddball task and gambling task that were randomized in order. All participants were run through all four tasks. We analyzed the third and fourth tasks for the purpose of this study as they pertain to working memory and feedback learning processes. We had no strong hypotheses for the first two tasks, as they had little relevance for our specific research question and as such the results of those tasks were not reported here.

The visual oddball task presented a series of common and rare (oddball) circles (see Figure 1). During the task, participants focussed their attention on a cross (5mm in diameter) fixated at the centre of a black screen. After a period of 300 to 500 ms, in which the cross was displayed, either a blue circle (common) or a green circle (rare) appeared on the screen. These circles (10 mm in diameter) appeared on the screen for a duration of 1000 to 1200 ms. The participants responded by actively pressing the "G" key when a green circle (rare) was presented. The rare circle was presented in 25% of infrequent trials and the common circle was presented in 75% of frequent trials. A total of 200 trials were completed, split into two blocks of 100 trials.

Figure 1

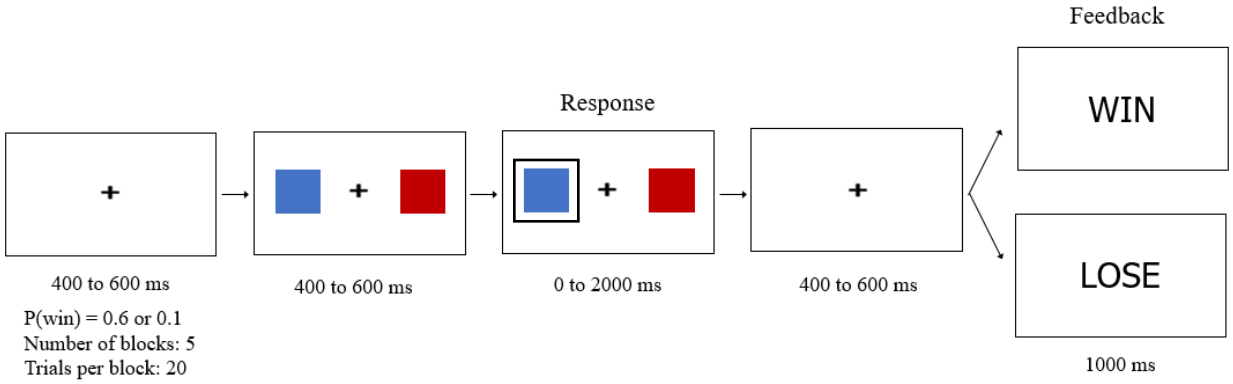
Displays of the visual oddball task in which the green circle represents the oddball trial, and the blue circle represents the control trial. Estimated times of each stimulus presentation is shown below each display image.



The gambling task presented two coloured squares and the participants chose one of the squares by either pressing the "F" key or the "J" key (see Figure 2). Once the square was pressed, participants were notified whether their choice was a "win" or "lose." One coloured square had a 10% probability of wins, and the other coloured square had a 60% probability of wins. These probabilities were randomized between different coloured squares for each block. The purpose of this task was to correctly identify which coloured square would result in the highest probability of wins. A total of 100 trials were completed across 5 blocks of 20 trials each.

Figure 2

Display of the gambling task, which includes two boxes of varying colours and differing probabilities of wins. Feedback was provided for whether the participant won or lost based on their selection.



Procedure and Data Collection

Prior to EEG set-up, participants gave written informed consent. Participants were then capped with the EEG system and filled out three questionnaires: a demographic questionnaire, the STAI, and the TICS-LE. Once capping was complete, instructions about the cognitive assessment tasks were given. Participants were then seated in front of a 19-inch LCD computer monitor to

perform tasks programmed using the Psychophysics Toolbox Extension (Brainard, 1997; Pelli, 1997) in MATLAB (Version 8.3, Mathworks, Natick, USA). All experiments were completed in a dark, quiet, and distraction-free room. The experiment took approximately 15 minutes to complete.

Using Brain Vision Recorder (Version 1.21.0004, Brain Products GmbH, Munich, Germany), a 32-electrode EEG system was used to record data. According to the International 10-20 system, the EEG cap was fitted with 30 electrodes and the remaining two electrodes were placed behind the participant's ears on the right and left mastoids. We should note that some participants were originally fitted with 64 channel electrode caps, and we later removed the 32 additional electrodes to ensure all participants had 32 total electrodes. To ensure that impedances were below 20kΩ, a conductive gel was applied to each electrode. The EEG data were online referenced to the AFz electrode, sampled at 500Hz, amplified (actiCHamp, Brain Products GmbH, Munich, Germany), and passed through a 245Hz antialiasing low-pass filter.

Data Pre-Processing

We used the standardized pipeline by the Krigolson Laboratory (available at https://www.krigolsonlab.com/data-analysis.html). Briefly, dead electrodes (channels with no electrical activity) and excessively noisy electrodes (channels with un-patterned, repeated large spikes unlike any other channel) were removed from processing. The data were re-referenced to the average of the right and left mastoid electrodes (TP9, TP10). A fourth order, zero-phase-shift Butterworth filter was applied with a low frequency cut-off of 0.1 Hz, a high frequency cut-off of 30 Hz, and a 60 Hz notch. Independent component analysis (ICA; Delorme & Makeig, 2004; Luck, 2005) was used to remove components indicative of blinks (large voltage changes concentrated at the front of the scalp); reverse ICA was then used on the removed components. Previously removed channels were added back using topographic interpolation (interpolation by spherical splines). From the 200 ms preceding the stimulus to the 800 ms after the stimulus, 1000 ms epochs of EEG data were constructed. These epochs were averaged for each channel and each participant to create the ERP waveforms. A baseline correction, using a -200 to 0 ms baseline prior to event onset, was applied to all trials. Trials were discarded if the voltage change exceeded 10 μV per sampling point or if the voltage was greater than 100 μV. On average 17.60%, 95% CI = [16.36, 18.84] of epochs were excluded from the oddball task, and 21.92%, 95% CI = [20.61, 23.23] of epochs from the gambling task.

In order to analyze the ERP components, we constructed a difference wave for both the P300 and reward positivity (Luck, 2014). The P300 component included segments for common and rare (oddball) stimuli from the visual oddball task. The P300 difference wave was constructed by subtracting the common-stimuli segment from the rare-stimuli segment. The reward positivity component included segments for win and loss stimuli from the gambling task. The reward positivity difference wave was constructed by subtracting the loss-stimuli segment from the win-stimuli segment.

Data Analysis

STAI and TICS-LE

Chronic stress levels were measured by determining mean negative affect scores using the Chronic Stress Screen Scale (CSSS) from the TICS-LE questionnaire. Higher scores indicate

greater amounts of chronic stress. The range of scores for the CSSS is 0 to 48. State anxiety and trait anxiety were measured by determining the mean negative affects scores using the STAI-S and STAI-T, respectively. Higher scores indicate higher levels of state and trait anxiety. The range of scores for the STAI-S and the STAI-T is 20 to 80.

P300 and Reward Positivity Components

The P300 and reward positivity peak amplitudes and latencies were measured for each participant from averaged ERP difference waveform data at electrode's Pz and FCz, respectively. To compute the amplitude of the P300, we found the peak of the grand average between 300 and 550 ms post-stimulus onset. We then used the peak of the grand average to compute each participant's mean peak using a window size of 100 ms around the grand average peak. For the reward positivity, we found the peak of the grand average between 200 and 400 ms post-feedback. We then used the peak of the grand average to compute each participant's mean peak using a window size of 96 ms. The existence of P300 and reward positivity were determined using single-sample t tests (Krigolson, 2018). Effect size was determined using Cohen's d using the following formula:

$$d = \frac{M_{diff}}{s_{diff}}$$

Where M_{diff} is the mean of either the P300 or reward positivity scores and s_{diff} is the standard deviation of the scores.

Correlations

Pearson correlation coefficients between each personality measure (chronic stress, state anxiety, and trait anxiety) and the P300 and reward positivity ERP component amplitudes were measured. In order to assess the significance of the correlations, we used a one-sample t-test.

For further exploration, we split the chronic stress, state anxiety, and trait anxiety scores into eight different quantiles (165, 150, 125, 100, 75, 50, 30, and 15). Commonly researchers will only sample a subset of participants, using various methods to define groups with high and low personality traits. For example, Zhang et al. (2015) defined trait anxiety scores based on being ± 1 SD of the mean, whereas Xia et al. (2017) used a percentage of the upper and lower distribution. The current study had a larger sample, meaning we had a continuous measure of P300 and reward positivity. Thus, splitting our data into quantiles allowed us to investigate different inclusion criteria and how the outcomes were affected as the quantiles start to represent the tail ends of the personality score distributions. Similar approaches of breaking large sample data into smaller quantiles have been done before in personality trait research (Jokela et al., 2013; Jokela et al., 2014). As the bin sizes decrease, we see a larger effect. We started with a bin size of 165, representing the median, and we dropped the middle 30 scores to get our next bin size of 150. Then we continued to drop the middle 50 scores to create bin sizes of 125, 100, 75, and 50. From there, we dropped the middle 40 scores, resulting in a bin size of 30, and finally, we dropped the last middle 30 scores to get a bin size of 15. For each quantile, representing the personality scores, we computed the mean differences, Cohen's d, Pearson's correlation coefficients with the P300 and reward positivity ERP component amplitudes. Additionally, we assessed the significance of the correlations for each bin size using a one-sample t-test.

Results

P300

The participants had a mean P300 amplitude of 6.34 ± 3.69 μV, 95% CI [5.93, 6.74]. A one sample t-test was conducted to compare whether the mean amplitudes were different from zero, $t(328) = 31.13$, $p = .00$, $d = 1.72$.

Reward Positivity

The participants had a mean reward positivity amplitude of 3.14 ± 4.18 μV, 95% CI [2.68, 3.59]. A one sample t-test was conducted to compare whether the mean amplitudes were different from zero, $t(328) = 13.62$, $p = .00$, $d = .75$.

Chronic Stress

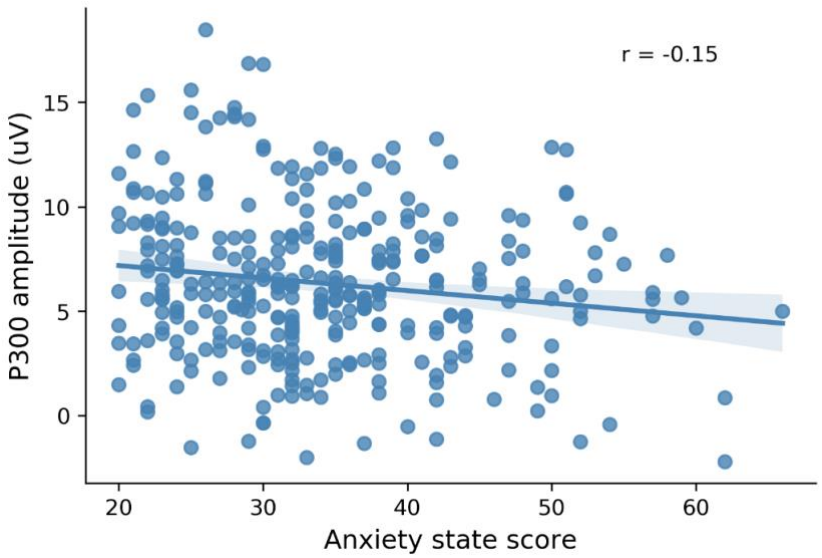
CSSS negative affect scores (M = 22.00, 95% CI = [21.08, 22.91]) and P300 amplitudes were found to be weakly negatively correlated, $r(328) = -.05$, but no significance was found, $p = .38$. CSSS negative affect scores and reward positivity amplitudes were found to be weakly positively correlated, $r(328) = .04$, but no significance was found, $p > .05$.

Anxiety State Score

STAI-S negative affect scores (M = 34.10, 95% CI = [33.09, 35.11]) and P300 amplitudes were found to be moderately negatively correlated, $r(328) = -.15$, $p = .01$ (Figure 3). STAI-S negative affect scores and reward positivity amplitudes were found to be weakly negative correlated, $r(328) = -.07$, but no significance was found, $p > .05$.

Figure 3

Negative correlation between STAI-S negative affect scores and P300 amplitude



Further, decreasing bin size of the anxiety state scores corresponded with increased mean differences, greater Cohen's d (Figure 4), and stronger negative Pearson correlation coefficients (Figure 5) of the P300 amplitudes (Table 1). Across all bin sizes, these correlations were found to be statistically significant (Table 1).

Table 1

Cohens d, Pearson's r, mean difference, and significance values of P300 amplitude with decreasing state anxiety quantiles

Quantile	M_{diff}	*d*	*r*	*p*
Median	-0.70	-0.19	-0.15	0.01
150	-0.78	-0.21	-0.16	0.00
125	-1.31	-0.35	-0.18	0.00
100	-1.44	-0.39	-0.21	0.00
75	-1.67	-0.45	-0.23	0.00
50	-1.73	-0.50	-0.26	0.01
30	-2.14	-0.54	-0.28	0.03
15	-3.02	-0.78	-0.39	0.03

Figure 4

Increasing effect size with smaller bin sizes of the anxiety state scores for the P300 amplitudes

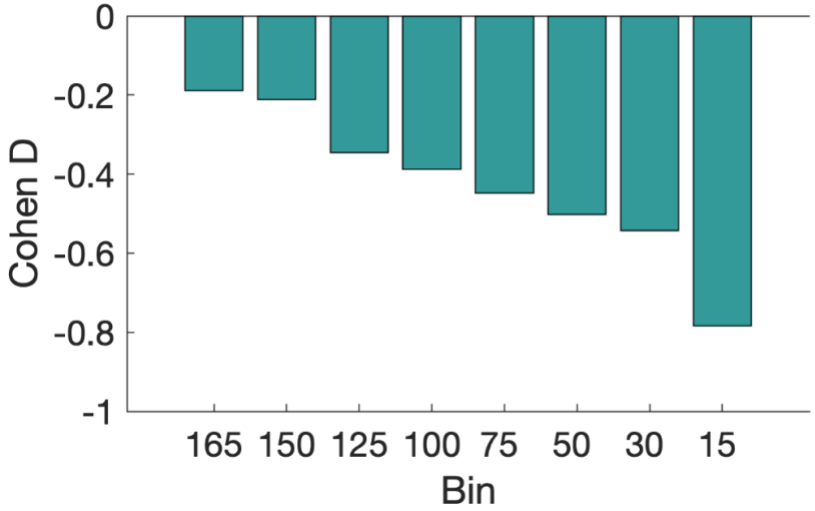
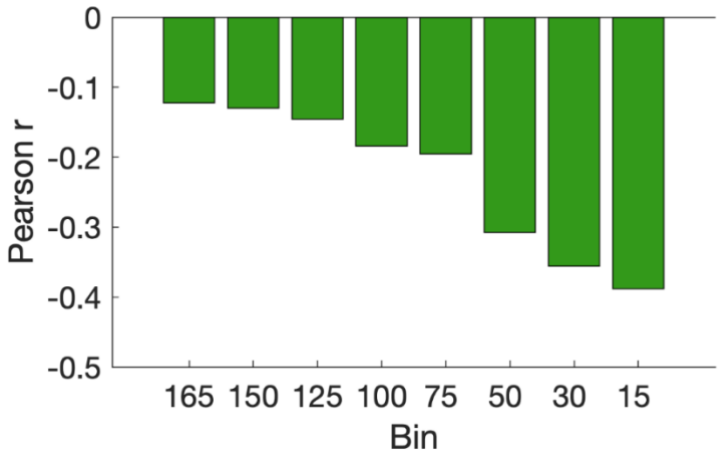


Figure 5

Stronger negative correlations of the P300 amplitudes with decreasing anxiety state score bin sizes.

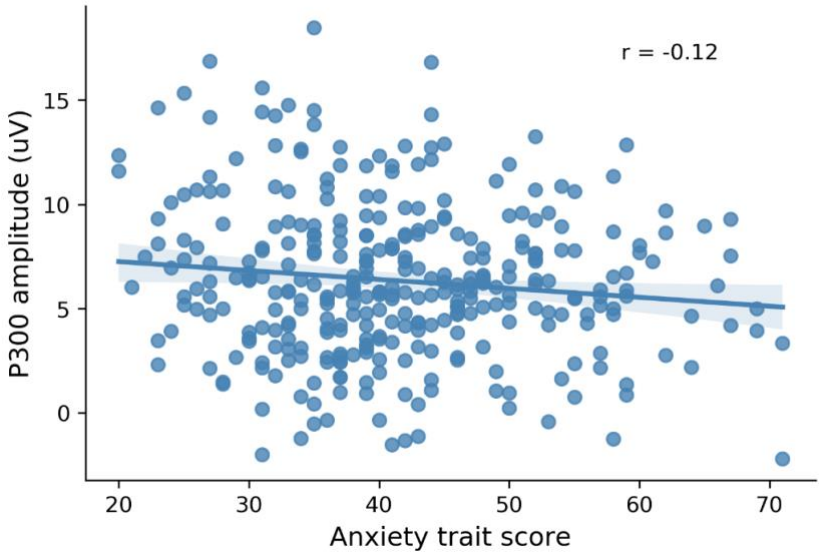


Anxiety Trait Score

STAI-T negative affect scores (M = 41.44, 95% CI = [40.29, 42.59]) and P300 amplitudes were found to be moderately negatively correlated, $r(328) = -.12$, $p = .03$ (Figure 6). STAI-T negative affect scores and reward positive amplitudes were found to be weakly positively correlated, $r(328) = .06$, but no significance was found, $p > .05$.

Figure 6

Negative correlation between STAI-T scores and P300 amplitudes



Decreasing the bin sizes of the trait anxiety scores corresponded with trends of increased mean differences, greater Cohen's d (Figure 7), and stronger negative Pearson correlation coefficients (Figure 8) of the P300 amplitudes (Table 2). Across all bin sizes, these correlations were found to be statistically significant (Table 2).

Table 2

Cohens d, Pearson's r, mean difference, and significance values of P300 amplitude with decreasing state anxiety quantiles

Quantile	M_{diff}	*d*	*r*	*p*
Median	-0.40	-0.11	-0.12	0.03
150	-0.47	-0.12	-0.13	0.02
125	-0.63	-0.17	-0.15	0.02
100	-1.21	-0.32	-0.18	0.01
75	-1.15	-0.30	-0.20	0.02
50	-2.24	-0.62	-0.31	0.00
30	-2.57	-0.70	-0.36	0.00
15	-2.36	-0.70	-0.39	0.03

Figure 7

Increasing effect size with smaller bin sizes of the anxiety trait scores for the P300 amplitudes

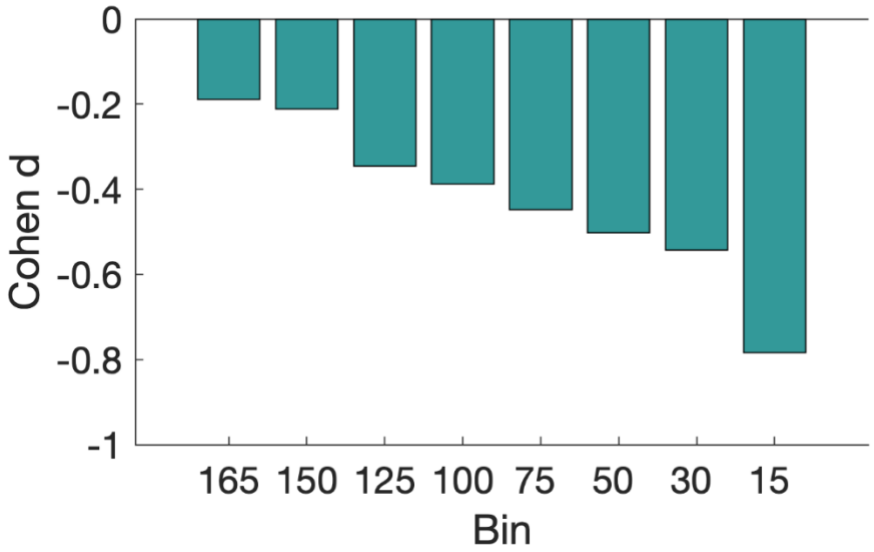
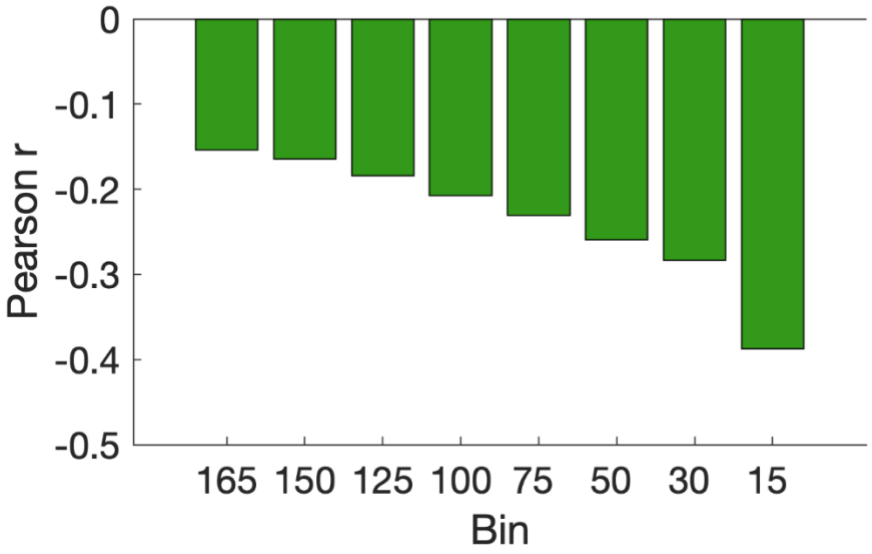


Figure 8

Stronger negative correlations of the P300 amplitudes with decreasing anxiety trait score bin sizes



Discussion

We found no significant effects of chronic stress, state anxiety, or trait anxiety on feedback learning. Additionally, no significant trends were observed for the effects of chronic stress on updating working memory. However, exploratory analysis revealed negative correlations in both state anxiety scores and trait anxiety scores and P300 amplitude. These effects were amplified with decreasing state and trait anxiety quantiles, resulting in greater mean differences, increased effect size, and moderate negative correlations of P300 amplitudes.

The findings of the current study support our hypothesis that as individuals experience greater levels of anxiety, there is a corresponding decrease in updating working memory processes. This relationship between anxiety and working memory processes has been supported in previous literature with smaller sample sizes. Specifically, in regard to state anxiety, Rossi and Pourtois (2017) observed a reduction in P300 amplitudes with increasing levels of state anxiety across 26 participants, as measured by the STAI-S. In regard to trait anxiety, Huang et al. (2009) observed dampened P300 amplitudes in 14 individuals who reported having high trait anxiety relative to 14 individuals who reported having low trait anxiety, as measured by the STAI-T. The results of the current study evaluated the relationship between varying levels of anxiety and changes in P300 amplitudes, demonstrating a similar trend of attenuated P300 amplitudes with increased anxiety scores. In addition, from a sample of 329 participants, we were also able to quantify this relationship between anxiety and updating working memory as moderately strong.

One consideration regarding anxiety research and the investigation of the neural correlates of decision-making is the methodological implications of sampling procedures. Anxiety research utilizing EEG methodology is commonly conducted using samples of undergraduate students

(rather than clinical populations with diagnosed anxiety disorders), and different methods are used to categorize anxiety levels within these students. Consistent with the current study, previous research has used the STAI to evaluate undergraduate participants' level of anxiety (Huang et al., 2009; Luo et al. 2018; Pederson & Larson, 2016; Rossi & Pourtois, 2017; Xia et al., 2017; Zhang et al., 2015). Often, within a cohort of participants, two groups are sampled for analysis: a high anxiety group and a low anxiety group. The methods used to distinguish these groups have differed across studies: Zhang et al. (2015) established the high and low trait anxiety groups based on scores being ± 1 SD of the mean, whereas Xia et al. (2017) used the upper and lower 25% of the distribution of anxiety scores. The varying definitions of high and low anxiety categories across studies raises concerns about whether populations are being consistently sampled and if these sampled groups are homogenous. Regardless of whether or not high and low anxiety scores are consistent across studies, it is apparent that if the goal is to examine the clinical/personality effects in the brain, researchers are interested in upper/lower ends of the distribution of scores.

Our analysis revealed that the majority of our undergraduate student sample did not report high or low anxiety scores, but rather fell within the middle range of scores for state and trait anxiety. In order to observe the effects of anxiety on updating working memory processes, we decreased the bin sizes of the state and trait anxiety scores to represent the upper and lower ends of the anxiety score distribution. We showed in our study that as the bin sizes decreased there was a stronger negative correlation between anxiety scores and updating working memory. Specifically, we saw that individuals who displayed greater levels of state and trait anxiety (upper end of the distribution) had lower P300 amplitudes indicating a reduced updating working memory process. The evidence from our study indicated that to understand how anxiety affects neural decision making in non-clinical populations, you must look at the extreme scores.

Our results are evidence of the beginnings of a correlation between anxiety and the neural correlates of decision making. Anxiety affects executive functioning by impairing cognitive control (Yang et al., 2018), attentional control (Derakshan et al., 2009), and causing structural and functional changes to the PFC (Fragale et al., 2016; Park et al., 2016). We are adding to the anxiety literature by using ERPs to observe the effects of anxiety on the neural correlates of decision-making. P300 is an ERP component that reflects the evaluation between current events with previous events in our working memory (Luck, 2014; Polich, 2007; San Martin, 2012). The attenuation of this ERP component is linked to higher susceptibility to impulsive decisions (Xia et al., 2017), interpreting stimuli as threatening (Luo et al., 2018; Pederson & Larson, 2016), and biasing attention towards negative stimuli (Huang et al., 2009) in anxious individuals. Our results showed that individuals with higher anxiety had decreased P300 amplitudes relative to individuals with lower anxiety. As such, greater anxiety levels were correlated with impaired working memory processes important for decision-making. The current study serves as a good stepping stone for future research to investigate the extent of alterations to executive functioning in clinical populations who exhibit higher levels of anxiety.

Conclusion

In an attempt to address the gaps in chronic stress and anxiety research, the purpose of the current ERP study was to explore the impact of chronic stress, state anxiety, and trait anxiety on neural decision-making processes including updating working memory and feedback learning. We hypothesized that we would see a reduction in P300 and reward positivity amplitudes with

increasing chronic stress, state anxiety, and trait anxiety scores. No correlations were observed for the three personality traits and reward positivity amplitudes, as well as for chronic stress and P300 amplitudes. However, our results demonstrated that state anxiety and trait anxiety were negatively correlated with P300 amplitudes, supporting our hypotheses. Anxiety appears to have an impact on our updating working memory processes, and this effect was increased when anxiety scores were binned to reflect the tails of the distribution. Due to the impact that chronic stress and anxiety can have on decision making, these personality traits have implications for many health conditions. Understanding how chronic stress and anxiety interact with neural processes that guide our behaviour offers insight into the difficulties that can arise from stress and anxiety.

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