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ABSTRACT

INVESTIGATING THE EFFECTS OF STRESS ON DECISION MAKING THROUGH THE LENS OF COGNITIVE NEUROSCIENCE

by

Elizabeth J. Pettit

To predict individual differences in decision making it is important to understand the cognitive processes involved, the underlying neural substrates, and how conditions of stress can alter those processes. The Iowa Gambling Task (IGT) is commonly used to study cognitive constructs necessary for risky decision making such as sensitivity to loss and the ability to learn optimization strategies over time. A number of computational models have had success predicting individualized decision making within this task and contain free parameters associated with these cognitive processes. Interestingly, neural data provided by electroencephalography (EEG) studies have shown frequency-band-specific event related oscillations (EROs) associated with similar processes. Thus, there seems to be great potential to link the neural data, behavioral data, and model formalization as they relate to individual differences in cognitive processes. The goal of the current project is to determine how neural patterns and behavioral parameters capture the change in the decision making process under stress. In this between subjects design, participant completed the standard IGT during a no stress condition or a stress condition using the Cold Pressor Task. While completing the IGT, an EEG was used to measure neural activity for comparison across these conditions. Behavioral model parameters of the best performing model were compared between the stress or no-stress condition. There was a significant interaction found between stress and gender on one computational modeling parameter as well as several main effects of gender, stress, and interactions between the two on power and coherence within and between neural regions. This project provides an innovative and powerful quantitative assessment of the neurophysiological and behavioral mechanisms underlying individual differences in how stress impacts risky decision making depending on gender.

INVESTIGATING THE EFFECTS OF STRESS ON DECISION MAKING THROUGH THE LENS OF COGNITIVE NEUROSCIENCE

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DEDICATION

This project is dedicated to my Grandma Jack (Jean Mangerson). I felt your little hand on my shoulder supporting me the whole way through.

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Introduction

No matter what career you choose, no matter how strict your daily routine, and no matter how thoroughly you practice “safe” habits, you will not be able to escape situations in everyday life that involve risky decisions and their associated consequences. For an extreme example, soldiers and surgeons have responsibilities of making risky decisions with impacts on how many lives are saved or lost. Over time, military and surgical personnel become more skilled at identifying which alternatives have a higher probability of leading to optimal outcomes. This decision process is altered under conditions of stress, a common attribute of the environment these professionals operate in. Although these extreme situations are of interest to this project’s funding agency (the Department of Defense), the phenomenon of altered risky decision making under conditions of stress can be observed in tasks as comparatively mundane as choosing between a new or familiar brand of pasta sauce at the grocery store or deciding whether or not to pause in the heat of the moment and take measures to practice safe sex. Understanding the cognitive processes in experience-based risky decision making, the underlying neural substrates involved, and how conditions of stress can alter those processes is important for improving and creating new neurocognitive decision making theories and interventions in many domains. This information could also be used to predict individuals’ decision making over time through the use of models guided by cognitive neuroscience.

Based on the examples given above, it’s clear that the definition of what constitutes a risky decision is quite broad. In decision science when comparing two alternatives in a choice the option with greater variability in outcome possibilities is typically defined as the riskier one. Colloquially this variability often has a negative connotation associated with it, however the variability could be amongst possible outcomes that are all positive in nature. In gambling paradigms like the one used in this experiment risk-seeking is operationalized as a preference for options with higher variability. Past research has shown that on average, people tend to make riskier experience-based choices when under conditions of stress induced by time constraint (Madan, Spetch & Ludvig, 2015).

Although behavioral data such as proportion of risky choices is useful in predicting a person's future decisions within the same paradigm, computational models are necessary to aid in understanding how the interacting cognitive processes involved in risky decision making are altered under conditions of stress to produce riskier choice behavior. These quantitative tools also aid in predicting how individuals will make decisions in a novel paradigm. Computational models contain variables called parameters that represent different cognitive process that are uniquely defined by each model and the theory that it simulates. These models typically follow the assumption that within conditions, choices on every trial arise from the same interaction of psychological process with static parameter values.

On the other hand, neural activity recorded with high temporal precision using an electroencephalogram (*EEG*) provides time-sensitive information about the changes in brain activity or cognitive processes involved in decision making. Innovative researchers such as Turner, Van Maanen & Forstmann (2013b) have combined information provided by neural activity to guide and improve our understanding of existing computational models of decision making. This experiment aims to accomplish a similar goal in an attempt to understand how power band-specific neural oscillations can be used to compliment computational models and the fluctuating psychological processes involved in experience-based risky decisions.

Motivation and rational for this experiment will be organized as follows. I will begin with a brief overview of the computational models proposed to simulate cognitive processes involved in the gambling task used in this experiment and why these computational models are invaluable tools to furthering theory in decision science. Next, I will review the neural activity past research has associated with risky decision making, more specifically within the Iowa Gambling Task. Afterwards I will review research focused on the neural markers of stress and its associated behavior changes. Finally, I will summarize the current experimental approach before jumping into methodology.

Historically, most decision science researchers have focused on the final outcome of a decision. Did the participant choose the first or the second option available? This provided a wonderful starting point to differentiate between advantageous and disadvantageous decision makers, or even to differentiate between risk-seeking and risk-averse decision makers. However, strictly studying the outcome of a decision does not allow researchers to determine *how* “good” versus “bad” decision makers come to their conclusions.

Within disadvantageous/bad decision makers specifically there could be several negative clinical consequences associated with poor decision-making skills. For example, risky behavior such as illegal substance abuse, unprotected sex practices, and gambling addiction are all in part the result of an inability to suppress choosing a small, immediate reward with negative long term consequences (Bishara et al., 2009). A common laboratory task, the Iowa Gambling Task (*IGT*; Bechara et al., 1994) has successfully been used to capture this inability and predict whether a participant displays one of the dysfunctional behaviors listed above. Unfortunately, participants with profoundly different disorders have the same decision outcomes characterized by choosing from disadvantageous decks associated with an average loss over time as opposed to learning to choose from the advantageous decks that are associated with an average gain over time. By analyzing the decision outcome alone the psychological processes that result in this disadvantageous decision style cannot be differentiated.

Instead, it's necessary to incorporate process methods to differentiate between groups of participants and help understand the cognitive processes responsible for the final decision. These process techniques can include computational models with variables called parameters that represent different cognitive processes with values unique to each population under investigation (Yechiam et al., 2005). In general terms, computational models use math as a universal language to represent activity in the brain and how cognitive scientists interpret that activity. Although criticized for being inherently abstract, computational models are not simply built by combining a number of complex equations and using algebra to solve for X. Instead, the equations are built using theoretical interpretations of findings from behavioral and neuroscience research.

For example, cognitive modelers have developed a representation for the psychological phenomenon of lateral inhibition through the combined contributions of behavioral and neuroscience research. In decision research lateral inhibition is observed when decision difficulty increases with the degree of similarity between two options. A decision is easier to make when your options are very different from one another as compared to when they are similar and difficult to distinguish between. Behaviorally, this has been represented by increasing deliberation time (Busemeyer & Townsend, 1993). In neuroscience studies it has been found that a specific neural structure, the basil ganglia, is an important structure when dealing with increasing degrees of lateral inhibition (Summerfield & Tsetsos, 2012). For example, typically when participants are presented with two stimuli that are easy to separate into different categories (low lateral inhibition) their decision time is shorter than when they are presented with two stimuli that are difficult to categorize (high lateral inhibition). However, individuals who undergo deep brain stimulation of the pathway between the cortex and basal ganglia will respond impulsively between two very similar options and fail to display the increased decision time that healthy controls exhibit (Frank, Samanta, Moustafa & Sherman, 2007). In math, degrees of similarity or the idea of lateral inhibition can be represented by a matrix with ones along the diagonal flanked by decreasing values until zeros are reached in opposite corners. This is just one demonstration of how human language, behavioral science, neuroscience, and math have all defined the same construct in different ways. They are all valid, and when combined together produce parsimony. This is exactly the goal of computational modeling: to represent cognitive processes in an abstract manner and define the interaction between these processes using mathematical relationships.

We can see the success of this approach in Decision Field Theory (Busemeyer & Townsend, 1993) which adopted the mathematical representation of lateral inhibition because behavioral and neural studies suggested that it was important player in the decision making process. The researchers did not simply try adding a new matrix and see if it worked- it was theoretically motivated. Studying decision making with a focus on the process rather than simply the decision outcome provides a wide variety of theoretical and practical advantages by allowing researchers to lift the cloak of invisibility that shrouds the mental processes associated with decision making.

There have been a number of computational models proposed over the years intended to capture the cognitive processes responsible for individual difference in behavior during the IGT, each with varying degrees of success (Lignuel et al., 2019). Although these studies have benefited from one process tracing tool, computational modeling, some have incorporated a second process tracing tool: electrical neural activity. Without cognitive modeling, neuroscience is unable to interpret results from a mechanistic point of view or address phenomena that require support beyond contrast analyses (Turner et al., 2017). On the other hand, without neuroscience cognitive modeling is inherently abstract and lacks falsifiability. Thus, I believe the two should be studied in concert and interpreted with patterns from each data source in mind. By allowing investigating both, we are not placing blind faith in a single approach.

Similarly, this project used neural data to help interpret existing computational models of the IGT. Once a viable model was identified, a quantitative relationship on the impacts of stress and gender on risky decision making was explored through participants' best fit parameter values. Using this knowledge in addition to neural activity changes while under stress I was able to make predictions and explanations for how and why stress may change decision making patterns. If we know which brain regions are involved in specific cognitive processes and what the underlying anatomical structure and connections are, we can develop more precise theories. This also allows cognitive scientists to discard theories and computational models that are not anatomically or neurochemically possible.

The next section explains the five computational models that were fit to the data. Each model is included in a MATLAB toolbox created by Dr. Lignuel (2019) and generously made available for other researchers to use (https://github.com/romainligneul/igt-toolbox). Though other computational models have been created to explain behavior during the IGT, these are currently the most prominent in the decision science literature.

Computational Models Under Comparison

The computational toolbox used in this experiment contains six models with unique parameters and with varying degrees of functional form complexity. Each model provides a different explanation for how and why people make decisions on reinforcement learning tasks such as the IGT. Included in this toolbox are two models that have both received criticisms for the validity of the cognitive processes and modules they propose (Konstantinidis, Speekenbrink, Stout, Ahn & Shanks, 2014; Haines, Bassileva & Ahn, 2018). Therefore I will only analyze the four models relevant to the neural focus of this project. Below I will provide a brief explanation of each model compared, accentuating the theoretical differences between them.

The first model, the Expected Valence Learning (*EVL*) model, has had varying success in accounting for behavior in the IGT (Busemeyer & Stout, 2002; Steingroever, Wetzels & Wagenmakers, 2014; Lignuel, 2019). According to this model, gains and losses experienced during the IGT elicit an affective reaction that the participant learns to associate with each deck through accumulated experience (Busemeyer & Stout, 2002).

Over time the decision maker begins to develop expectancies about these affective reactions known as valences. Each time a deck is chosen, its valence is used to update the decision maker's expectancies about the deck's outcome by averaging over all past experiences with that deck. If that deck is not chosen on a given trial, its' expectancy is not updated. One model parameter, the recency parameter, *r*, indicates the amount of weight given to the most recent experiences when learning the expected outcome of each deck. Participants with a higher recency parameter tend to place greater weight on most recent events and exhibit less learning and short associative memories (Busemeyer & Stout, 2002). On the other hand, a different model parameter, λ, indicates how sensitive the participant is to experiencing losses in comparison to experiencing gains. Participants with a higher λ are very sensitive to experiencing a loss and tend to choose from the advantageous deck more often (Bishara et al., 2009). The final parameter is a measure of choice consistency, or how consistent a person's choices are with the outcomes they've experienced thus far. A higher value indicates choices that are highly consistent with expected values whereas a lower value indicates choices inconsistent with learned expected values. All three models included in the current analysis include a choice consistency parameter with the same interpretation.

In recent years the EVL model has failed to find support in some cases (Steingroever et al., 2014) and varying success in others (Lignuel, 2019). In part, this lack of fit may be due to the models' linear utility function as opposed to the consistently supported Prospect Utility function (Tversky & Kahneman, 1992). According to this function, decision makers display diminishing sensitivity to outcomes as magnitude increases and possess different sensitivity for receiving losses as compared to gains. In addition, in the EVL model only the deck chosen on that trial receives an update to its expected utility, while all other unchosen decks remain unchanged. This violates the Decay learning rule (Erev and Roth, 1998) which predicts that the expectancies of unchosen decks should be discounted. Therefore, our second model under comparison, the Prospect Valence Learning model (*PVL*; Ahn, Busemeyer, Wagenmakers, & Stout, 2008; Ahn, Krawitz, Kim, Busemeyer, & Brown, 2011), included both of these repeatedly supported theoretical additions. It should be noted, however, that the PVL model has also received recent skepticism when compared to competing models (Steingroever, et al., 2014; Lignuel, 2019).

Our third model, the PVL-Delta model (Ahn et al., 2008; Fridberg et al., 2010) considers the delta learning rule within the EVL model instead of the Decay learning rule, but otherwise maintains all other updates included in the PVL model. As explained above, according to the Delta learning rule (Rescorla and Wagner, 1972; Sutton and Barto, 1998; Yechiam and Busemeyer, 2005). the expected values for each option are recency-weighted averages of the rewards received on each trial. The expected value of unchosen decks remains unchanged, as opposed to the Decay learning rule which assumes that expected values for each option decay on each trial (Erev and Roth, 1998). The PVL-Delta model contains two parameters necessary to include Prospect Theory's prediction for diminishing sensitivity to increases in magnitude and different sensitivity for losses as compared to gains. One parameter determines the shape of this utility function, or how quickly a person becomes desensitized to large magnitude outcomes. People with low values for this value sensitivity parameter would be expected to prefer decks with high win frequency over decks which win less often (Haines et al., 2018). A second parameter determines the sensitivity to experiencing a loss, with higher values indicating greater sensitivity. Deck expectancies are updated according to the Delta rule which assumes that participants' expectancy for each deck is composed of a recency-weighted average of all experiences for that deck thus far. Again, higher recency parameter values indicate a greater weight placed on recent outcomes and forgetting distant experiences. The PVL-Delta successfully generated behavioral choice patterns across multiple data sets using the simulation method in Steingroever, et al., (2014).

However, in the same paper (Steingroever et al., 2014), a newly proposed model, the Value plus Sequential Exploration (*VSE*) model, was able to outperform all others I've previously discussed. The VSE model will serve as the fourth model included in the current comparison. Although lacking a loss aversion function, this model includes "exploitation weights" that keep track of recent trends in gains and losses similar to previous models. Similar to the PVL-Delta model, this includes a value sensitivity parameter with low values indicating a preference for decks with high winning frequency over decks with equivalent expected value but which win less often. A decay parameter controls the rate at which the exploitation weight returns to zero, with a value of 1 indicating that exploitation weights are integrated over all previous trials. The VSE model also benefitted from the addition of an "exploration weight" associated with each deck (Lignuel, 2019). This addition was motivated by the observation that some participants exhibit an exploration pattern of choosing each of the 4 decks in a repetitive, 4 choice sequence. This is similar to directed exploration observed in a class of multi-armed bandit rodent tasks from which the IGT descends (Daw, O'Doherty, Dayan, Seymour & Dolan, 2006). Within this module, the explore learning rate parameter controls how fast the exploration weight of a given deck bounces back to its initial bonus, drawing participants to choose that deck. Another parameter, the explore bonus is specific to each participant and can be positive or negative, depending on whether they prefer to explore or avoid options not recently chosen. Negative values indicate that the person tends to favor familiar decks whereas a positive value suggests the decision maker is attracted to decks which have not been recently explored. On each trial, exploitation and exploration weights are summed before being transformed into choice probabilities using a conventional SoftMax step (Ligneul, 2019). The deck with the highest choice probability is most likely to be chosen.

As mentioned, the VSE model is missing a parameter to represent one cognitive concept that is consistently supported by decision research: loss aversion. For this reason, a version of the model that includes a loss aversion parameter similar to that used by the PVL model was also analyzed. This model, the VSE-LA model, served as the fifth and final model included in the current analysis.

Past research has had success tying specific brain regions and electrical activity to cognitive processes represented by parameters in the models discussed in this section. One of the most prominent theories used to explain behavior during the IGT is known as the somatic marker hypothesis. It states that physical, emotion-based signals bias the response of higher order brain regions involved in decision making including the prefrontal cortex (Bechara, Damasio, Tranel & Damasio, 1997). Though not a formal computational model, research pursuing the somatic marker hypothesis led to many experiments investigating the neuroscience behind the IGT. The following section provides a brief review.

Neurobiology of Risky Decision Making and the Iowa Gambling Task

Risky decision making has been a common focus in value-based decision research because it allows for the separation between two attributes of risky decision stimuli: reward amount and outcome probability. By separating these two attributes of a decision, neurobiologists can distinguish between the brain mechanisms that contribute to each. This allows greater precision in determining the cause of maladaptive risky choice. However, like most neuroscience research, ethics and funding constraints prevent direct manipulation and measurement of human brain activity. Luckily, rodent models of the IGT have been developed with varying pay-out probabilities and represent loss of reward through quinine-laced food pellets or time-outs from sugar pellets (Heilbronner, 2017). Though the task is clearly not identical to the human version of the IGT, rodent behavioral responses, neural activity (de Visser, Homberg, Mitsogiannis, et al., 2011) and learning curves appear consistent with human's (van den Bos, Lasthuis, Den Heijer, Van der Harst, & Spruijt, 2006).

A combination of studies produced by rodent- and human-subject labs has led to an accumulation of evidence for the dominant brain regions involved during the IGT. The affective loop is thought to be composed of the amygdala, ventral striatum/nucleus accumbens, orbitofrontal cortex (OFC), and ventromedial prefrontal cortex (vmPFC), whereas the executive cognition loop is thought to be composed of the dorsolateral prefrontal cortex (dlPFC) anterior cingulate cortex (ACC), and dorsal striatum (Koot, Baars, Hesseling, van den Bos, & Joels, 2013). Because this experiment uses neural data collected using a non-invasive technique, I will provide the greatest amount of focus on brain areas closer to the surface of the skull where the EEG is able to provide a more accurate measure.

As prefaced, the somatic marker hypothesis has often been used to guide research investigating the affective experience of receiving a loss during the IGT. Included in the affective loop is the vmPFC, a region involved in the integration of information from the limbic system and basal ganglia (Bechara, Damasio, Damasio & Lee, 1999; Sanfey, Rilling, Aronson, Nystrom & Cohen, 2003). Past experiments have found participants with lesions to the vmPFC consistently display deficits in decisions related to losses and gains (Bechara et al., 1994;). Humans with vmPFC damage have displayed increased levels of risk taking (Bechara et al., 1994; Damasio et al., 1994) and within the IGT specifically have shown a strong myopia for distant consequences (Bechara et al., 1994).

Nearby, also contained in the affective loop, the OFC assists in evaluation and filtering of perceptual and emotional information (Elliott, Dolan & Frith, 2000). This connectivity network with the limbic system, basil ganglia, and sensory association cortices suggests that the OFC may use salient information from the environment to assign a value to a reward/loss and signal outcome expectancies (de Visser, et al., 2011). Support for this hypothesis is provided by an experiment in which OFC lesioned animals displayed higher levels of risk seeking behavior during the second phase of the rodent IGT (Pais-Vieira, Lima & Galhardo, 2007). However, the literature has also suggested that the OFC may play a more rational, objective role by converting stimulus values into a common currency that allows for straightforward comparison (O'Dougherty, 2007).

Within the executive cognition loop lies the dlPFC which I cannot describe in relation to decision making without also discussing the ACC. Deep within the brain, the

ACC signals error likelihood and plays a key role in combining probability with the costs and benefits of each option in the choice set (Hunt et al., 2018). The dlPFC assists the ACC in updating information about each option by temporarily maintaining currently/recently attended information and detecting outcome consequences (de Visser et al., 2010). The dlPFC has also been found to represent stimulus features and location (Hunt et al., 2018), which may feed into the ACC to help produce an action/choice.

This top-down, executive cognitive control network has been suggested to mediate the second part of the IGT after participants have begun to learn which decks are advantageous or disadvantageous (de Visser et al., 2011). Neuroimaging studies have found gender differences while completing the IGT where good performing men showed greater activation in the right OFC compared to women, and women showed greater activation in the dlPFC compared to men (Bolla, Eldreth, Matochik, & Cadet, 2004). This suggests that there may be individual differences in brain areas recruited to accomplish decision making in contexts involving uncertainty.

Most human subjects experiments investigating the relationship between neural activity and cognitive processes associated with risky decision making have analyzed event-related potentials. However, this analysis of averaged data provides less information on the frequency-specific cognitive processing than can be obtained using the fine-grained wavelet-based frequency analysis of EROs (Makeig, Westerfield, Jung, Enghoff, Townsend, Courchesne, et al., 2002). In short, these analyses indicate whether characteristics (e.g. amplitude, frequency) of regular oscillations in electrical brain activity change across conditions, and whether they are correlated across brain regions.

Past research using gambling tasks have found different types of activity in the theta, beta, and gamma power bands when a participant experiences a loss relative to a gain. Gehring and Willoughby (2004) found frontally focused theta activity (4-7 Hz) during decision conditions associated with a loss and Cohen et al., (2007) reported enhanced power and cross-trial phase coherence in the theta band for losses as compared to gains. Inversely, enhancement of activity within the beta band (20-30 Hz) has been found for gains relative to losses (Marco-Pallares, Cucurell, Cunillera, García, Andrés-Pueyo, Münte, et al., 2008). A study by DePascalis et al., (2012) investigated EROs for the theta (4-8 Hz), beta (13-25 Hz), and gamma (30-40 Hz) activities in response to losses or gains during a reinforcement learning task. They found an increase in theta-band activity across the midline frontal and central brain regions during a loss. In contrast, in response to a gain, the authors found an increase in beta and gamma-band activity over frontal, prefrontal and posterior scalp regions. These findings suggest that theta activity within frontal regions such as the vmPFC and OFC may be related to individual differences in sensitivity to loss and computational model parameters that may represent it.

Just as DePascalis et al., (2012) found brain oscillation activity related to sensitivity to losses or gains, the authors also found supporting evidence for EROs related to performance. Specifically, they found that theta (4-8 Hz) and gamma (30-40 Hz) oscillations play a leading role in the learning process as compared to beta. Good performers displayed increased intra and interhemispheric synchrony in the gamma band when experiencing a loss during the second stage of the task as compared to the first. In contrast, bad performers showcased decreased gamma synchrony between fronto-parietal and occipital regions in response to a loss. Other studies have found evidence that increased gamma band activity is involved in learning (Miltner, Braun, Arnold, Witte, & Taub, 1999) and an increase in gamma band coherence between distant brain regions suggests communications, allowing integration of information thus resulting in learning (Steriade, 2006). Therefore, posterior regions and their communication with the frontal regions already discussed will be examined in the current experiment.

To reach a beneficial decision in risky contexts like the IGT, people must learn strategies by evaluating each alternative based on its outcome (Brand, Labudda, & Markowitsch, 2006). However, environmental-, organism-, and task-dependent factors can have profound effects on how decisions are made. For example, it is well known that stress, whether chronic or acute, impacts decision making in numerous ways. But how does stress uniquely impact different cognitive processes such as learning and sensitivity to loss and their corresponding neural circuits?

Neurocognitive Effects of Stress on Risky Decision Making

Stress within an organism occurs when the demands of the task surpass the ability of the organism and when the task has an emotionally engaging and unpredictable component to it (Starcke & Brand, 2002). In rodent models, the induction of stress is typically accomplished through a physical hardship (foot shocks, fasting), a social/emotional hardship (isolation, rejection), or the injection of the stress hormone, typically cortisol. For humans we have to take a more ethical, short term approach to stress induction. This is typically accomplished through time pressure, difficult cognitive activities (math, logic problems), social evaluation, slight physical discomfort (Cold Pressor Task), or, uncommonly, the application of a stress hormone, typically hydrocortisone (Starcke & Brand, 2002). Within humans, more often than not we are restricted to noninvasive techniques to monitor brain activity in response to stress. On the other hand, in rodent models we are able to utilize invasive techniques such as recording single neural cell activity or creating lesions within the brain regions we believe to be necessary or sufficient components in stressed reactions and affected behavior. Both approaches assume high overlap between humans and non-human animals regarding brain regions and their anatomical connections. Although the methods and participants between these two fields are vastly different, they are converging on a clear view of how stress impacts the brain.

Early research on the impacts of stress on decision making focused on changes in behavior. For example, exposing participants to high levels of stress resulted in search termination meaning participants decided on an option before evaluating every alternative for potential outcomes (Janis & Mann, 1977). In another laboratory experiment, compared to non-stressed participants, those who were stressed made more risky, disadvantageous decisions that lead to potentially high reward but frequent punishments (Starcke, Wolf, Markowitsch & Brand, 2008). These findings were supported by a study in which one half of participants in the sample were administered 40 mg of hydrocortisone to induce stress, resulting in a greater number of high-risk gambles with potential for both high reward and loss (Putman, Antypa, Crysovergi & van der Does, 2010).

More recent studies on the impacts of stress on decision making have explored changes in neural activity. When a situation is interpreted as stressful, the HPA axis is activated and neurons in the hypothalamus release a cascade of hormone/NT communications to the pituitary and next to the adrenal glands in order to release stress hormones (Lupien et al., 2007). Several studies have found high overlap between the brain regions involved in decision making and those impacted by stress (Starcke & Brand, 2012). For example, fMRI indicated that acute stress leads to metabolic reactions in the prefrontal, limbic, basal ganglia, and other brain regions (Lupien et al., 2007). Stress has been shown to decrease activity within the OFC, hippocampus, and hypothalamus (Pruessner, Dedovic, Khalili-Mahani, Engert, Pruessner, Buss, et al., 2008) and to increase activity in the dlPFC, ACC, basal ganglia, and ventral striatum (Pruessner, Champagne, Meanes, & Dagher, 2004). Due to the vmPFC's dense connectivity with the basal ganglia, which increases in activity during stress (Starcke et al., 2012), it is no surprise that stress has been found to decrease performance on the IGT (Starcke et al., 2012). In an experiment by Henckens et al., (2011), cortisol administration resulted in improved working memory capacity by slow corticosteroid actions as opposed to fast actions, and this improvement was related to increased activity in the dlPFC. These studies provide converging evidence that stress has a unique impact on the affective and cognitive neural loops involved in the IGT.

However, the evidence is not as transparent as the previous paragraph suggests. Mixed results have been reported, but with certain consistencies that lead me to believe individual differences may be at play. In some cases, stress increased activity within the amygdala, thalamus, and insular cortex and in other cases stress decreased activity (Starcke & Brand, 2012). When considering the plausible list of individual differences responsible, sex appears to be a great candidate. The most common neural sex difference that I've encountered concerns the greater hemisphere crosstalk within the female brain as opposed to the male brain (Bolla et al., 2004). On average, women perform worse on the IGT, or at the very least take a greater number of trials to reach performance similar to men (van den Bos et al., 2013). Gender differences in choice sequence suggest women may utilize different cognitive strategies during risky decision making (van den Boss, 2013).

Gender differences in brain activity while completing the IGT have also been observed (Northoff et al., 2006; Tranel et al., 2005; van den Boss et al., 2013). During stress conditions, men have been found to display greater risk-taking as compared to women (Starcke et al., 2012). van den Bos et al., (2013) performed a study where they separated participants depending on the severity of their cortisol response to a stressor. In men, those who were highly reactive to the stressor displayed a decrease in IGT performance compared to low reactive men and controls. On the other hand, highly reactive women displayed an initial increase, then an eventual decrease in performance compared to low reactive women and controls. A study by De Visser et al. (2010) used a similar paradigm but investigated how level of trait anxiety impacted IGT performance differently depending on sex, as opposed to stress reactivity. In De Visser et al., (2010) men with both low and high trait anxiety showed impaired performance whereas only high anxiety women showed similar impairment.

Support for sex differences is also supported by neural studies where men (not women) with damaged right prefrontal (not left prefrontal) areas displayed decreased performance during the IGT (van den Bos et al., 2013). These differences are of interest to the current proposal because the right prefrontal areas have been more tightly linked to stress as compared to the left prefrontal areas (Starcke et al., 2012). Thus, van den Bos et al., (2013) have suggested that the improvement in women's performance may be due to enhanced right prefrontal activity driven by the effects of cortisol. These studies suggest that there are neural underpinnings responsible for sex differences in response to stress, however the differences are not always harmful to female performance as exemplified by van den Bos et al., (2013). We need to take a more nuanced view by considering individual differences in reactivity and neuroanatomy. The following section will explain the approach this experiment used to accomplish just that.

Experimental Approach

The goal of the current experiment was to determine how neural activity and behavioral parameters capture the change in the decision making process under stress. For this between-subjects experiment, half of the participants completed the IGT while under no stress, and half completed the IGT in a state of stress due to a Cold Pressor Task manipulation. At three different points participants provided a self-report of their current stress level. Participant's 120-choice sequence were fit to five computational models to assess model performance and obtain a set of parameter values for each participant. While completing the IGT, participants' brain activity, specifically frequency-band activity, was collected using an EEG. By collecting two sources of data, behavioral and neural, this methodological approach provided an example of how neurophysiological data can improve explanations of fluctuations in cognitive processes under conditions of stress.

Method

For this experiment a total of 93 participants were recruited. Though this is admittedly a bit large for an EEG study, it was necessary to counterbalance gender (male or female), and stress or no-stress condition. 21 participants' data were unusable due to equipment error or excessive motor movement on part of the participant, obscuring the majority of neural activity related to cognitive processes. Out of the 73 total participants 19 were in the female, no stress condition; 19 were in the male, no stress condition; 18 were in the female, stress condition; and 16 were in the male, stress condition.

To participate, students chose this study from a list of available experiments at Miami University to serve as a subject in exchange for research credit hours. Experience with an EEG is unique among undergraduates and may provoke anxiety within the participant. To alleviate this concern, an email was sent to each participant the day before they were scheduled containing a short video walking them through the processes of participating in a study that uses EEG, showing that no pain will be experienced and that it is an interesting, educational process.

Once the participant entered the lab, they received a short description of the experimental tasks and an informed consent to sign. To allow acclimation to the testing environment, the participant first answered a set of three different questionnaires used to explore individual differences that may account for variation in risky decision making behavior. First was the Edinburgh Handedness Inventory (Oldfield, 1971), a questionnaire recommended in any EEG study to aid in separating neural activity due to motor movements related to providing a response versus that due to cognitive processing. This is a short, 12 item inventory with daily activities about which the participant responds whether they use their left or right hand to complete. Activities include writing, brushing one's teeth, eating with a spoon, etc. Next was Eysenck's Impulsivity Inventory (Eysenck & Eysenck, 1978) containing 61 yes/no statements designed to measure levels of impulsiveness, venturesomeness, and empathy. Of specific interest to the current study is impulsivity, previously related to developing a successful strategy to perform well on the IGT (Giustiniani, Joucla, Bennabi, Nicolier, Chabin, Masse, Trojak, Vandel, Haffen, & Gabriel, 2019). Last in this block of questionnaires was the Multiple Stimulus Types Ambiguity Tolerance inventory (*MSTAT-I*; McLain, 1993) with 22 items assessing one's tolerance for ambiguity. Considering the expected value and riskiness of each deck in the IGT is never stated to the participant, there is a large level of ambiguity surrounding how "good" each option is. Different people may find this more aversive than others would, possibly impacting decision making behavior.

Next participants provided their first heartrate recording, referred to as timepoint A. This was designed to serve as a physiological measure of stress. In addition, participants were given a 10 point scale on a piece of paper asking them to indicate their stress level with 1 being no stress at all and 10 being the greatest stress imaginable. While sitting in a chair with their feet flat on the ground, participants rested their nondominant hand on a table while a pulsometer is attached to the tip of their middle finger. For one minute they remained still while their pulse was recorded using a heartrate pre-setting in Lab Scribe. The recording device was a PT-104 pulse plethysmograph connected to an IWorx acquisition unit. This timepoint was intended to serve as the participants' resting heart rate and a benchmark for the experimenter to ensure the participant returns to before leaving the lab.

Participants were then fit with a 256 channel Electrical Geodesics Hydrocel sensor EEG net. While netting, the experimenter gave a general explanation of the task that follows: “Next, you’re going to complete a sort of gambling game. During the task, please try to relax shoulders and not move around too much. These movements cause a lot of noise in the EEG data and make it difficult to see the cognitive activity we’re interested in. For the game, there will be more detailed instructions on the screen before you begin, but you’ll essentially be trying to gain as much “money” in your bank as you’re able to based off which shapes you choose. Over time you will learn which shapes are good and are more likely to win you money over time, and which shapes are bad, and more likely to lose you money over time. These “good” and “bad” identities stay the same throughout the entire task, so you don’t have to worry about them switching on you. For every 500 “dollars” you earn, your name will be entered into a raffle to win one of four 50$ Amazon gift cards. So, try to earn as much as you can.” Funds for these performance incentive gift cards were drawn from my Fall 2021 Graduate Student Achievement Award.

Meanwhile in another room, if the participant was assigned to the stress condition, a research assistant (*RA*) prepared materials for the Cold Pressor Task. This involves filling a large bowl with water, adding a handful of ice cubes, and stirring until the temperature reached 13 degrees Celsius. Following netting, in both conditions participants were led to the testing room containing a desk with a monitor to display the IGT, a “keyboard” with 5 buttons, the first 4 corresponding to the 4 IGT decks, a video camera, and a stationary chair. Participants were seated in the chair and their net connected to the recording arm. Electrodes were scrubbed until they reached below 50 KΩ.

While I improved impedance, if the participant was in the stress condition, the RA explained, “During the first part of this gambling task you’re going to complete the Cold Pressor Task which requires you to place your hand in very cold water. You will complete the task twice-now, while you’re reading the instructions and completing a few practice trials, then again after you finish the gambling task. While you complete the task, your facial expressions will be recorded on the video camera here. A panel of experts will analyze and score your reactions at a later time.” This information was an act of deception to increase stress levels experienced by the participant. Though their facial reactions were recorded, this recording was not saved and was never analyzed. Also, the participant did not complete the Cold Pressor Task (*CPT*) a second time.

When instructions were complete, the experimenter left the testing room and turned off the lights. In the no-stress condition the RA also left the room, but in the stress condition they remained in the room and administered the CPT. To do so, they explained to the participant “For the Cold Pressor Task, you will put your hand in this bowl of water up to your wrist. You should feel the bottom with your fingers. Try not to move your hand. Try your hardest to keep your hand in the water for the entire duration of the task, which is expected to take about 12 minutes. If you do need to remove it, you may simply let me know and I will help you guide it out onto this towel.” The RA then guided the participant’s hand to the bowl of water. There was a box with a towel in front of the water bowl for the participant to rest their arm and eliminate additional motor movement. During this time, the experimenter began the EPrime program running the IGT in the recording room and tried to time this to begin exactly when the participants' hand reached the water. Noise traveling easily between the testing and recording room made this possible. If the participant was not in the stress condition, the experimenter began the EPrime program immediately after leaving the testing room.

Participants were first presented with a short written explanation of the task with performance incentives explained and were told they would begin with a few practice trials. This took about 30 seconds to read. For four practice trials, participants chose from the four shapes shown in Figure 1 located directly in the middle of the screen. These shapes are used and formatted in this way for IGT EEG studies to reduce the number of ocular artifacts recorded. Participants had an unlimited amount of time to choose, but typically provided a response in less than 10 seconds. After each response feedback was displayed including their total bank amount (beginning with $2000) and the outcome of their most recent choice. Pay-off matrices for each deck/shape are included in Table 1, mirroring those used in (Bechara et al., 1994). When a deck was chosen, each row in Table 1 had an equal probability of being randomly drawn, determining that trial's payoff and reflecting uncertainty of negative outcomes in the real world. In typical versions of the IGT there is both a win and a loss outcome displayed. However, in the current experiment I have added together that trial's win and loss to display an outcome total. This decision was made in an effort to reduce visual search and ocular artifacts that may interfere with recording brain activity related to cognition. Though this is a notable alteration to the task, all participants repeatedly experienced different amounts of wins and losses, just not in tandem. This allowed for greater separation of brain activity in response to a loss as opposed to a win, and vice versa. After feedback was displayed, there was a 2000 ms intertrial interval before the 4 options were available on screen to choose from again.

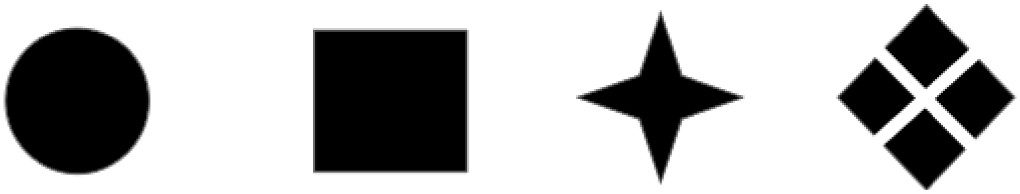

Fig. 1 IGT stimulus layout. Each shape corresponds to the four decks used in the traditional IGT.

Table 1

IGT Payout Matrix

	Circle	Crystal	Square	Diamond
	100	100	50	50
	-200	100	50	50
	-50	100	0	50
	100	100	50	50
	-250	100	0	50
	100	-1150	50	50
	100	100	0	50
	-150	100	50	50
	100	100	0	-200
	-100	100	0	50
EV	-250	-250	+250	+250
Risk	Low	High	Low	High

After four practice trials, lasting about 30 seconds, a new instruction screen appeared informing participants that the next part would be the actual experimental task and to ask the experimenter if they had any remaining questions. All participants then clicked through the entire experiment on their own time. If the participant was in the stress condition, the RA continued to monitor the participant for any signs of physical distress (change in breathing patterns, concerned facial expressions, intense fidgeting, etc.) and removed the participants hand if they deemed intervention necessary. Fortunately, this situation never occurred. In total, only 3 participants removed their hand from the water due to the uncomfortable cold temperature. Their data were not removed from analyses.

Once the participant completed all 120 trials of the IGT, lasting approximately 10-12 minutes, the experimenter re-entered the testing room. The EEG net was disconnected from the recording unit and wrapped in a protective towel. While the participant remained netted, a second heartrate measure was taken back in the main testing room, referred to as Timepoint B. The same steps were repeated as for Timepoint A, including a 10-point stress scale question. Once recording was complete, if the participant was in the stress condition, the RA explained that they did not need to complete the CPT a second time and that we mislead them to increase their stress reaction.

Next was completion of the second block of individual differences questionnaires. First was the Need for Cognition Scale (Cacioppo & Petty, 1982) designed to measure a person's tendency to engage in and enjoy thinking. The somatic marker hypothesis has linked decision making in the IGT to a gut-feeling or visceral reaction and scoring high on the Need for Cognition Scale conflicts with that style of decision making. Second was the Spheres of Control Scale (Paulhus, 1983), a 30 point scale used to measure a persons' perceived control in different areas of life. Third was the Adult-Decision Making Competency scale (Bruine de Bruin, Parker & Fischhoff, 2007), specifically the 20 question Risk-Perception Consistency component. Lastly, participants completed a short demographic questionnaire including gender, age, race, year at Miami and SES.

Finally, a third heartrate measure was taken, referred to as Timepoint C, and following the same protocol as the previous two timepoints. If the participant had returned to a heartrate near their Timepoint A measure, and they were not displaying any visible signs of distress, the experimenter continued to the debriefing process. Here I explained that any video recordings would be promptly deleted if they were in the stress condition. Participants were provided with a debrief form and the instruction to watch their email for a notification following all data collection to find out if they won a gift card. The entire experimental process took approximately 90 minutes.

Analyses & Results

Stress Scale and Heartrate

To determine whether subjective stress was successfully induced through the stress manipulation, participants' Timepoint B subjective stress rating (scale from 1-10) was subtracted from their Timepoint A rating. Using this difference, a negative score suggested a decrease in subjective stress rating and a positive difference suggested an increase in stress. A repeated measures ANOVA was conducted to determine whether there was a significant effect of gender and stress condition on this difference. There was no significant interaction between gender and stress condition on subjective stress rating (F(1, 66) = .248, p=.620), or main effect of gender on subjective stress rating difference (0.305, p=.583), or main effect of stress condition on subjective stress rating over time (.099, p=.754). This suggests that the stress induction attempts such as the cold pressor task and recording participants' facial expressions during the experiment were not successful at inducing higher levels of subjective stress ratings as compared to participants assigned to the no-stress condition. Ironically, males in the stress condition reported a mean decrease in stress of 0.31 points (SE=.418; Fig 2), but an increase in stress when part of the no stress condition (M=0.294, SE=.405). On average, females in the stress condition reported the largest mean increase in subjective stress rating between Timepoints A and B (M=.389, SE=.394) followed by females in the no stress condition (M=.316, SE=.383).

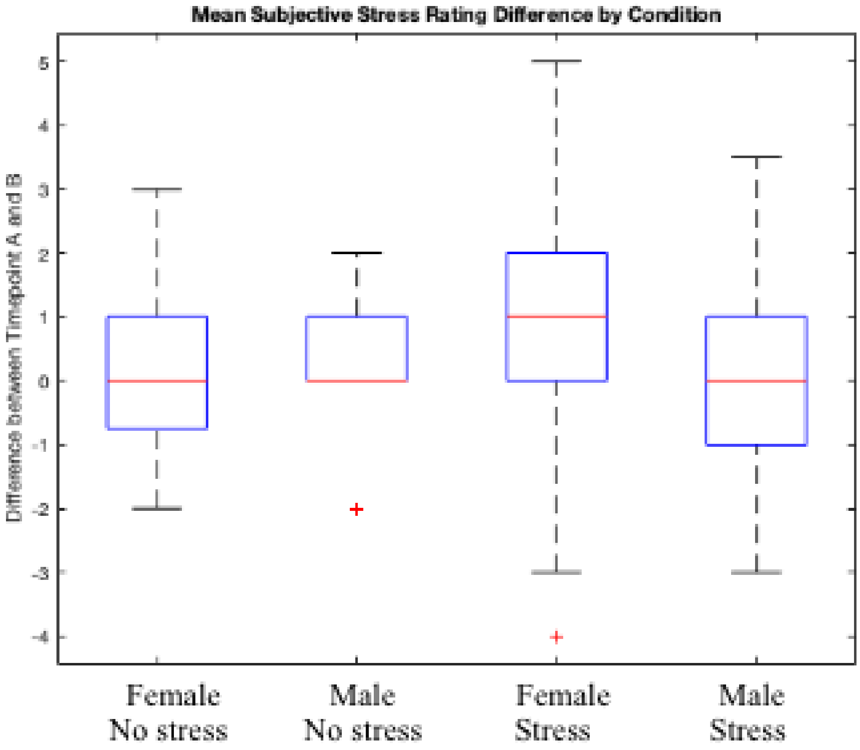

Fig 2. To see whether subjective stress was successfully induced through experimental manipulation, participants' Timepoint B subjective stress rating was subtracted from their Timepoint A rating. Using this difference, a negative score suggests a decrease in stress and a positive difference suggests an increase in stress. No significant differences were found between condition or gender.

When looking over participants' mean subjective stress rating at each of the three timepoints, there appeared to be an expected stressful impact from simply participating in a research experiment. Across both conditions and genders, the last timepoint, C, had the lowest average subjective stress rating (M=2.71, SD=1.71). The middle timepoint, B, had the highest average subjective stress rating (M=3.16, SD=1.85), which is reasonable considering all participants have just had an EEG net placed on their head and completed a gambling task in a dark room. The first timepoint, A, had an average subjective stress rating of 2.93 (SD=1.96), which is again reasonable considering they may have been nervous about any experimental tasks they were anticipating.

Complimenting the subjective stress scale was a physiological measure of stress: heartrate. Unfortunately, equipment error resulted in excessive interference, rendering the heartrate data unusable. For this reason heartrate results will not be discussed.

Behavioral Measures

A few different behavioral measures were calculated from participants' 120 trial choice sequence during the IGT. All analyses were calculated using the IGT toolbox from Ligneul (2019). First, net score was determined by subtracting the number of times the disadvantageous decks were chosen (A and B) from the number of times advantageous decks were chosen (C and D). Individuals that end the task with a positive score are considered to display "good" decision making behavior and individuals with a negative score indicate "poor" decision making. Females in the no stress condition (n=19) had the lowest mean score of -4.00 (*SD*=32.00; Fig. 3), followed by males in the no stress condition (n=19) with a mean score of 0.32 (*SD*=44.04). Females in the stress condition had the second highest score (n=18) with a mean score of 3.44 (*SD*=36.97), and males in the stress condition (n=16) had the highest score of 5.13 (*SD*=40.74). A two-way ANOVA was performed to analyze the effect of gender and stress condition on net score. There was not a significant interactions between gender and stress (F(1, 68) = 0.021, p=.89). There was also no significant main effect of stress (0.451, p-value=.50) or gender on net score (0.108, p=.74).

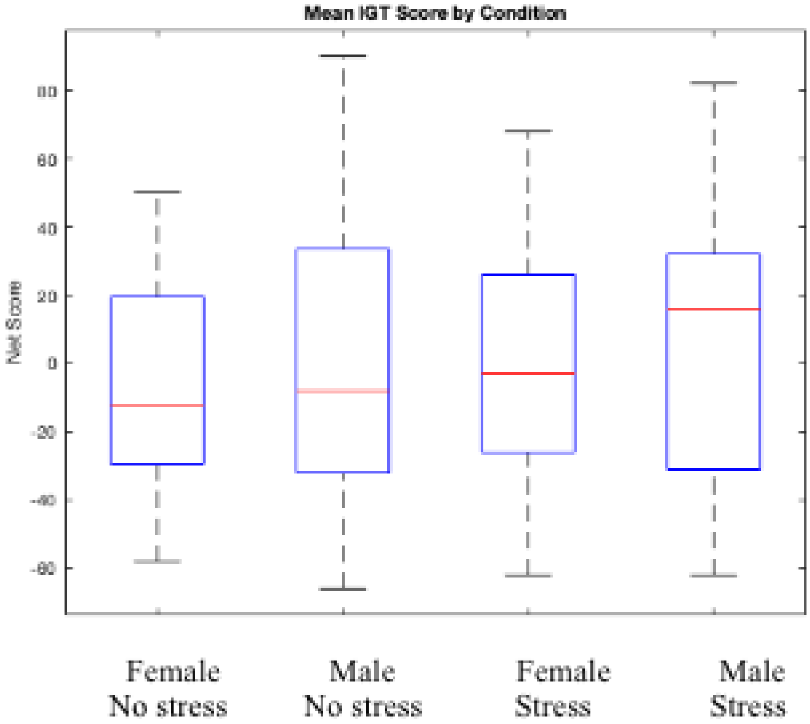

Fig. 3 Mean net score for each condition. Net score was calculated by subtracting the number of times the disadvantageous decks were chosen (A and B) from the number of times advantageous decks were chosen (C and D). Individuals that end the task with a positive score are considered to display "good" decision making behavior and individuals with a negative score indicate "poor" decision making. No significant difference was found between stress condition or gender.

Two additional variables included in the toolbox are called win-stay (WS) and lose-shift (LS). These variables reflect the proportion of trials in which participants selected again the same deck after an outcome which involved no loss (WS) and the proportion of trials in which participants selected a different deck after an outcome involving a loss (LS). A two-way ANOVA was performed to analyze the effect of gender and stress condition on win-stay strategy use but there was no significant interactions between gender and stress (F(1,68) = 0.33, p=.57) or main effects of stress (0.05, p-value=.82) or gender on WS score (0.03, p=.87). A two-way ANOVA also did not reveal a significant interaction between gender and stress (F(1,68) = 0.934, p=.33) on the use of the lose-shift strategy. There was no significant main effect of stress (0.71, p-value=.40) or gender (0.40, p=.53). on LS score.

The last behavioral measures indicated the amount of directed exploration (DE) that many rodent models have investigated and which drove the VSE model's development. DE3 and DE4 are the model-free measures of directed exploration that correspond respectively to the frequency at which participants selected 3 different decks over 3 consecutive trials (DE3: theoretic chance level:0.3333) or 4 different decks over 4 consecutive trials (DE4: theoretic chance level at 0.0938). Participants' mean DE3 and DE4 scores per condition are shown in Appendix A. Two more two-way ANOVAs were conducted to investigate whether gender and stress had an effect of the directed exploration of three or four available options, but no significant interactions or main effects were found (Appendix B).

Individual Difference Questionnaires

Each individual difference measure was scored following original methods. A short descriptions of high and low scores once normalized will be provided here. The Edinburgh Handedness Inventory (Oldfield, 1971) contains 12 items about which the participant chooses from a 5 point scale with 1 being "strongly left handed" and 5 being "strongly right handed". Thus, a minimum score of 12 points suggests the person is highly inclined to complete tasks left handed whereas a maximum score of 60 points suggests the person is highly inclined to complete tasks using their right hand. However, the questionnaires were structured so that participants were not forced to answer every question included, in a cautious attempt to avoid making participants uncomfortable with disclosing any information they are uncomfortable with. For the Edinburgh Handedness Inventory, 3 participants failed to answer one of the 12 questions making a minimum score of 11 points and a maximum score of 55 points. Therefore, all scores were normalized so that a value of 100 suggests a strongly right handed person and a score of 0 suggests a strongly left handed person. A score of 50 suggests a perfect ambidextrous person. For this sample, participants answered with a mean score of 81.14 (*SD=14.69*) suggesting that on average, they were predominantly right handed.

Eysenck's Impulsivity Inventory (Eysenck & Eysenck, 1978) containing 61 yes/no statements, some of which are reverse coded. 24 items are associated with the impulsiveness subscale, 17 with venturesomeness, and 20 with empathy. Again, scores were normalized so that a value of 100 represents that a person scored as high as possible on each subset, whether it be impulsiveness, venturesomeness, or empathy. A score of zero suggests that the person does not display that individual difference subset of impulsivity to any degree. Participants in this sample displayed a mean venturesomeness score of 55.44 (*SD*=20.56), suggesting moderate levels of willingness to take on risk or embark on new experiences. They showed a mean empathy score of 72.31 (*SD*=14.52), suggesting an above average level of empathy, or ability to understand or share the feelings of another. Regarding impulsivity, they had a mean score of 39.35 (*SD=19.35),* suggesting a moderate tendency to take time and think critically before taking action.

The Multiple Stimulus Types Ambiguity Tolerance inventory (*MSTAT-I*; McLain, 1993) contains 22 items assessing one's tolerance for ambiguity, some of which are reverse coded. Participants answer using a 7 point Likert scale with a 1 meaning "highly disagree” and 7 “highly agree”. A minimum score of 22 (0 after normalization) suggests a person is intolerant of ambiguous situations whereas a maximum score of 154 (100 after normalization) suggests a person is highly tolerant of, and possibly enjoys ambiguous situations. Participants in this sample displayed a mean score of 63.60 (*SD*=8.97) suggesting moderate to high levels of tolerance for ambiguous or uncertain situations or environments.

The Need for Cognition Scale (Cacioppo & Petty, 1982) contains 44 items designed to measure a person’s tendency to engage in and enjoy thinking. Participants respond with the degree to which they highly disagree (1) with the written statement, up to highly agree (9). Again, some items are reverse coded. A minimum score of 44 (0 after normalization) indicates low enjoyment of or need for cognition whereas a high score of 396 (100 after normalization) indicates great need and enjoyment in thinking activities. Participants in this sample showed a mean score of 63.99 (*SD*=8.513) suggesting a moderate to high need for mental stimulation and critical thinking.

Second is the Spheres of Control Scale (Paulhus, 1983), a 30 point scale used to measure a persons’ perceived control in personal efficacy, interpersonal conflict, and sociopolitical control, with each subscale containing 10 items. Participants rate the degree to which they agree (7) or disagree (1) with each statement using a Likert scale. Within each subscale a low score of 10 (0 after normalization) suggests the person does not feel the need for control in that area of their life, whereas a maximum score of 70 (100 after normalization) suggests they feel as though they need complete control in that area. Participants in this sample had a mean score of 72.64 (*SD*=10.76) for personal efficiency, suggesting a moderately high need for control over their nonsocial environments. They had a mean interpersonal control score of 68.08 (*SD*=9.84) which represents a moderate to high need for control over other people in dyads and groups. For the final subcategory of the Spheres of Control Scale, sociopolitical control, participants in this sample displayed a mean score of 53.23 (*SD*=12.74) suggesting a moderate need for control over social and political events and institutions.

Last is the Adult-Decision Making Competency scale (Bruine de Bruin, Parker & Fischhoff, 2007), specifically the 20 question Risk-Perception Consistency component. For the first ten questions the participant indicates on a scale from 0 to 100 how likely it is that a certain event in occur in the next year. The next ten are the same events, but instead the participant rates how likely the event is to occur in the next 5 years. Participants receive a point for consistency each time their 1 year rating is equal or less than likely to occur than the 5 year rating. A score of 0 points suggests a person has very low risk perception consistency and a maximum score of 10 (100 after normalization) indicates a person is highly consistent in their risk perception. Participants in this sample showed a mean score of 79.99 (*SD=7.49*) suggesting moderately high consistency with their perception of risk over time.

Relationship between behavioral measures and individual differences

To explore whether there were any relationships between behavioral metrics on the IGT and any of the individual differences collected during the experiment, a series of Pearson's r correlations were run between each individual difference measure and each behavioral variable. The only relationships to show significance at the .05 level or below were subsections of Eysenck's Impulsivity Inventory (Eysenck & Eysenck, 1978). First, there was a weak, negative correlation between impulsiveness and net score on the IGT (r=-.311, p<0.1) suggesting that participants who are more impulsive were likely to end up with a lower score or perform worse on the IGT. Additionally, more impulsive individuals were less likely to utilize the win-stay strategy or continue to choose the same deck after it provides a positive outcome, as supported by the weak negative correlation between impulsiveness and win-stay scores (r=-.243, p=0.04. Second, empathy had a weak negative correlation with participant's directed exploration of four decks (D4) score (r=-.237, p=0.045). This suggests that more empathic individuals were less likely to use the strategy of choosing all four available decks in the same order, over a four trial period throughout the task.

Computational Modeling

Computational models were fit to the data using the IGT Toolbox available from Lignuel (2019). This toolbox relies on a Variational Bayesian scheme that informs the optimization algorithm with a prior distribution of parameter values. The toolbox includes an automatic setting for all parameters for every model which defines priors as a Gaussian distribution with a mean of 0 and variance of 3. This places the uniform distribution over the 0-1 interval after transformation using a sigmoidal function. According to the toolbox, each parameter for each model is allowed to uniquely vary according to the range of pre-set values, and the sigmoid-transformed parameters will be further stretched or shifted to cover different intervals. Model performance was compared using the Bayesian Information Criterion (BIC) calculated by the toolbox. Typically a lower BIC indicates better fit, however the toolbox transforms BIC values to BIC* = -BIC/2 in order to obtain log-evidences. Therefore, in the following results a higher BIC* indicates a better fit.

The EVL model had the worst fit with an average BIC* of -120.73 (*SD* = 24.54), followed by the PVL-Delta model which resulted in an average BIC* of -119.73 (*SD* = 25.33). The PVL model resulted in an average BIC* of -115.07 (*SD* = 26.38, and the VSE-LA model had an average BIC* of -114.32 (*SD* = 20.06). The VSE model displayed the best fit by a small margin with an average BIC* of -111.78 (*SD* = 25.31).

An additional way to analyze model fit is to count the number of times a model produces the highest BIC* for a participant. Out of all 73 participants run, one data file could not be analyzed due to a technical error. Across the remaining 72 participants, 29 were best fit by the VSE model, followed by the EVL model that best explained 15 participants choices. The PVL model had the highest BIC* for 13 participants and the PVL-Delta model for 9 participants. The VSE-LA model performed the worst and was the best fitting model for only 6 participants. It is worth noting that the rank order of these models are at odds depending on whether you are comparing the average BIC or the number of participants with the lowest BIC. However, due to the VSE model's superior performance on both statistics, it will be used to illustrate how to interpret its best fitting parameter values among the entire sample of participants.

First, the value sensitivity parameter showed a mean best fit value of 0.32 (*SD* =0.20). With a possible range of 0-1, this suggests that on average participants are more likely to prefer decks with high win frequency over equivalent decks which win less often. The inverse decay parameter also has a range of 0-1, and for the current data set produced a mean best fit value of 0.62 (*SD* = 0.27). This value slightly above the midpoint suggests that participants do rely on most recent outcomes to make decisions, but they also integrate some information over previous trials. In other words, they appear to fall somewhere in between both extremes. The explore learning rate parameter determines how quickly the exploration weight of a deck returns to its initial bonus sampling value, and again, has a possible range of 0-1. The mean best fit value for this parameter was also slightly above the midpoint, M = 0.59 (*SD* = 0.24). The exploration bonus parameter (unbounded) had a mean best fit value of 0.09 (*SD* = 2.52). Although not far above zero, this positive value suggests that on average participants were attracted to decks that had not been explored recently. Lastly, the mean choice constancy parameter was *M* = 0.82 (*SD* =0.65). This means that on average, participants were responding quite randomly, and inconsistent with expected values experienced thus far. For a breakdown of each parameters' mean best fit value for each condition, please refer to Appendix C.

A series of two-way ANOVAs were performed to analyze the effect of gender and stress condition on participants' mean best fit VSE model parameter values. Only one parameter showed a significant relationship: the explore alpha parameter. There was a significant interaction between gender and stress (F(1,68) = 4.367, p=.04) on the explore alpha parameter, used to control how quickly a participants' inclination to explore available decks rather than exploit a familiar one grows. There was no significant main effect of stress (0.07, p=.933) or gender (1.345, p=*.25*). on mean explore alpha parameter values. When looking at Figure 4 you can see that males in the stress condition had the lowest explore alpha parameter value of 0.491(*SD=.059*) but males in the no stress condition had the second highest value of .612(*SD=.054*). Women showed an opposite effect of stress with a mean explore alpha parameter value in the stress condition of 0.671(*SD=.055*) while the no stress condition had a mean value of 0.560(*SD=.054).* This suggests that when males are placed under stress, they are slower to build an inclination to explore options that haven't been chosen recently as compared to when they are not under stress. On the other hand, females under stress will more quickly build an inclination to explore options that haven't been chosen recently as compared to when they are not under stress.

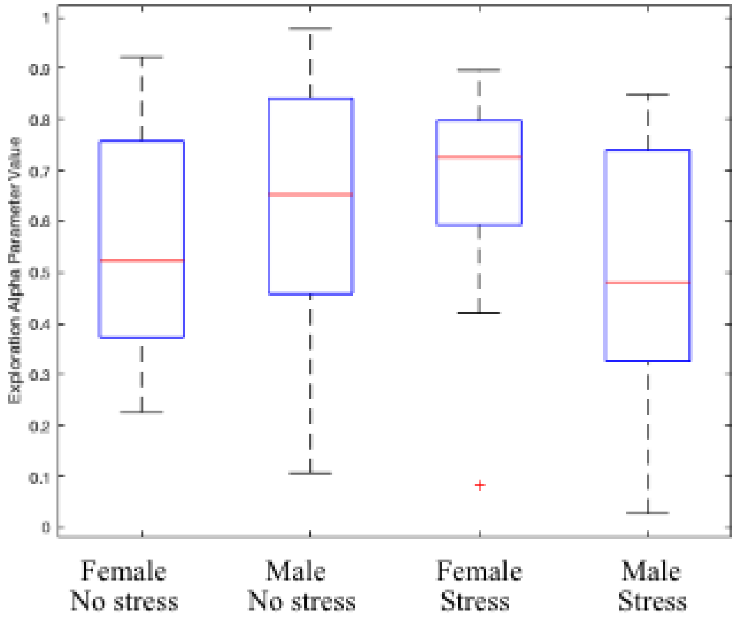

Fig. 4 Mean best fit exploration alpha parameter value from the VSE model for participants included in each condition. Larger values of the explore learning rate suggest the person will quickly build an inclination to explore options that haven't been chosen recently.

Four additional two-way ANOVAs were conducted to investigate the effects of gender and stress on the remaining four parameters in the VSE model, however no significant interactions or main effects were found (Appendix D).

Relationships between behavioral measures and model parameters

To explore whether there were any relationships between behavioral metrics on the IGT and participants' best fit VSE parameter values, a series of Pearson's r correlations were run. Only relationships that showed significance at the .05 level or below are discussed. First, there was a weak positive correlation between net score and participants' best fit inverse decay parameter (r=.253, p=.03) suggesting that individuals who perform better on the IGT are likely to exhibit greater learning rates, or integration of past experiences into their current decision. There was a moderate, negative correlation between participants' win-stay score and their explore bonus parameter (r=-.540, p<.000), meaning that individuals who more often used the strategy of sticking with a deck after it produces a positive outcome are less likely to explore all four available options and more likely to continue choosing a familiar deck. On the other hand, there was a strong positive correlation between the explore bonus parameter and lose-shift scores (r=.713, p<.000). Participants who more often use the strategy of shifting away from a deck after it produces a negative outcome are more likely to explore all four decks available rather than sticking with one familiar one. Lastly, the lose-shift variable also revealed a moderate positive correlation with the choice constancy parameter (r=.473, p>.000), suggesting that individuals who use the strategy of switching away from it deck when it doles a loss show decision making consistent with expected values experiences thus far.

Relationships between individual differences and model parameters

To explore whether there were any relationships between individual difference measures and participants' best fit VSE parameter values, a series of Pearson's r correlations were run. Again, only relationships that showed significance at the .05 level or below are discussed. First, there was a weak positive correlation between a person's empathy score and their explore alpha parameter value (r=.265, p=0.03). This suggests that individuals that have a strong ability to understand another person's emotions are likely to quickly build an inclination to explore options that haven't been chosen recently. Second, venturesomeness scores revealed a weak positive correlation with participants' value sensitivity parameters (r=.250, p=.03), meaning that individuals with a high willingness to take on risk or embark on new experiences are more likely to prefer options that produce large outcomes more frequently over those that produce small, frequent outcomes. Lastly, the choice constancy parameter also showed a weak, positive correlation with participants' personal control scores (r=.357,p<.01), suggesting that individuals who feel a greater need for control over their personal life and actions are also more likely to make decisions consistent with the expected values they have so far experienced.

Neural Activity

Though there are many different possible analyses for the neural data that was collected, I focused on areas that point to individual differences in reaction to stress or areas that the literature has reported conflicting results on. Of course, the data must first be cleaned. Neural activity was recorded using Netstation then imported to the EEG Lab toolbox in MATLAB. First, a high pass filter with a lower edge of 1 Hz was used, then averaged over all channels using a reference electrode. Next, ICA decomposition was used and component maps were classified by the default algorithm to assist in labeling artifact components such as motor movements or eye blinks which were removed from the data. Between 10-20 components were removed per participant. A low pass filter with a higher edge of 45 Hz was then applied before the data file was uploaded to Netstation once again. The entire data file was visually inspected and bad channels were manually marked and replaced after again being transferred to EEG Lab. Next, the entire data file for each participant was visually inspected for bad segments, or periods of time during the experiment where interference or significant motor movements created noise that rendered the data unusable. These segments were cut from the data files. Finally, trials were categorized based off the epoch window.

There were two epoch windows of interest, one concerned with electrical activity contributing to the decision process (referred to as the decision process epoch) and the second concerned with activity related to processing the outcome, or feedback, from the decision (referred to as the feedback epoch). Both epochs were response locked where the time of response serves as timepoint 0 (Figure 5). For each trial, all four shapes/decks were available to the participant to on the screen until a decision was made. However there was a 2000 ms intertrial interval (*ITI*) after feedback to allow a controlled gap between trials. Therefore, even though each participant may have taken a different total amount of time to make a decision for each trial, this first window was captured between 1000 ms before the response was made (sometimes drifting into the ITI feedback) until 800 ms after the response was made at which time the screen was blank for the 1000 ms ITI after the choice. Baseline correction used the first 200 ms of each segment. The second window, feedback, captured neural activity 100 ms before the outcome was displayed to the participant (900 ms after a response was made) up until 2000 ms after outcome display (3000 ms after response was made). Again, baseline correction used the first 200 ms of each segment.

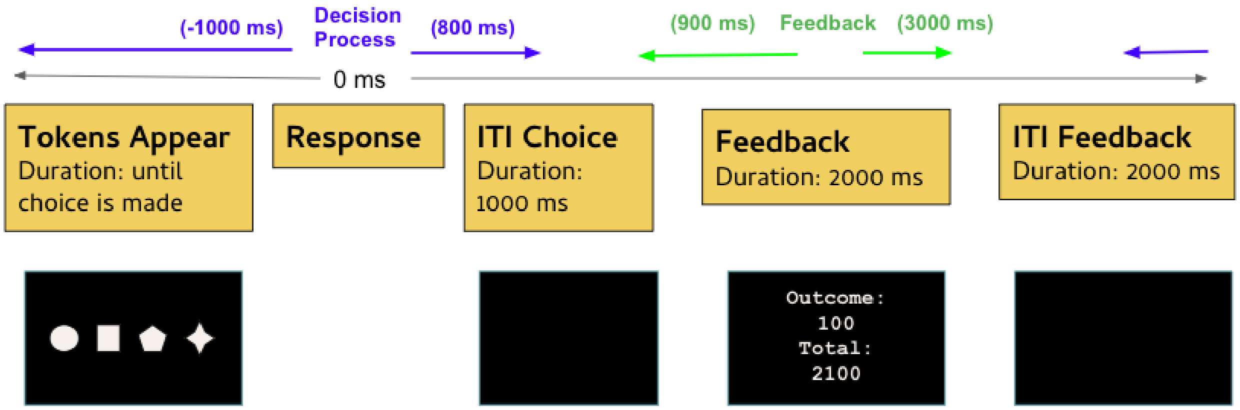

Fig. 5 Timing of stimulus display as programmed in EPrime. Epoch windows are shown above for the decision process time period in blue and for the feedback time period in green.

Afterwards, time-frequency analyses were performed. Power within each band and inter-site phase synchrony were calculated using a fast Fourier transformation (FFT), which performs a Fourier transform within a time window that is moved along the time series in order to measure changes in power and phase of a signal over time. To use this approach a few parameters needed to be set. First, each of the six brain regions of interest were defined by a cluster of channels as shown in Figure 6. Next was the upper and lower frequency bound. I also needed to define the number of frequency bins which determines the resolution of the frequencies examined. However, there are limitations to keep in mind when defining these bins. First, the lower bound frequency must be greater than the epochs of the data, as defined by the formula 1/t where t is time length of segment in seconds. This means that if the segment length is 1 second, none of the bins can contain a frequency value less than 1Hz. For the current experiment, the epochs lengths were 1800ms for the decision process window and 2100ms for the feedback window. This allows for a 1Hz lower bound on all trials. Second, the upper bound is the Nyquist limit, or half of the sampling frequency. With this data collected at 250Hz, the upper bound limit was 125Hz. However, this is much higher than the frequencies under investigation related to cognitive activity, especially considering the lab equipment produces ambient electrical noise at frequencies between 55-60Hz. Thus, the upper bound limit was set to 45Hz. The final parameter to define was number of cycles, which involves a tradeoff decision between resolution in the time domain and precision in regard to frequency. There are a few different gold standards for a reasonable compromise (Cohen, 2014) but for the current analysis 5 cycles was used. Using this method, for each trial I calculated the average power measured in squared Hz per unit frequency for each of the six brain regions of interest within each of the three frequency bands of interest. Those bands were defined as [3.5-7.5] Hz for the theta band, [11.5-29.5] Hz for the beta band, and the gamma band was allowed a range of [30-45] Hz. For each participant a grand average amplitude was calculated for each band (3), for each brain region of interest (6), for both epoch windows of interest (2).

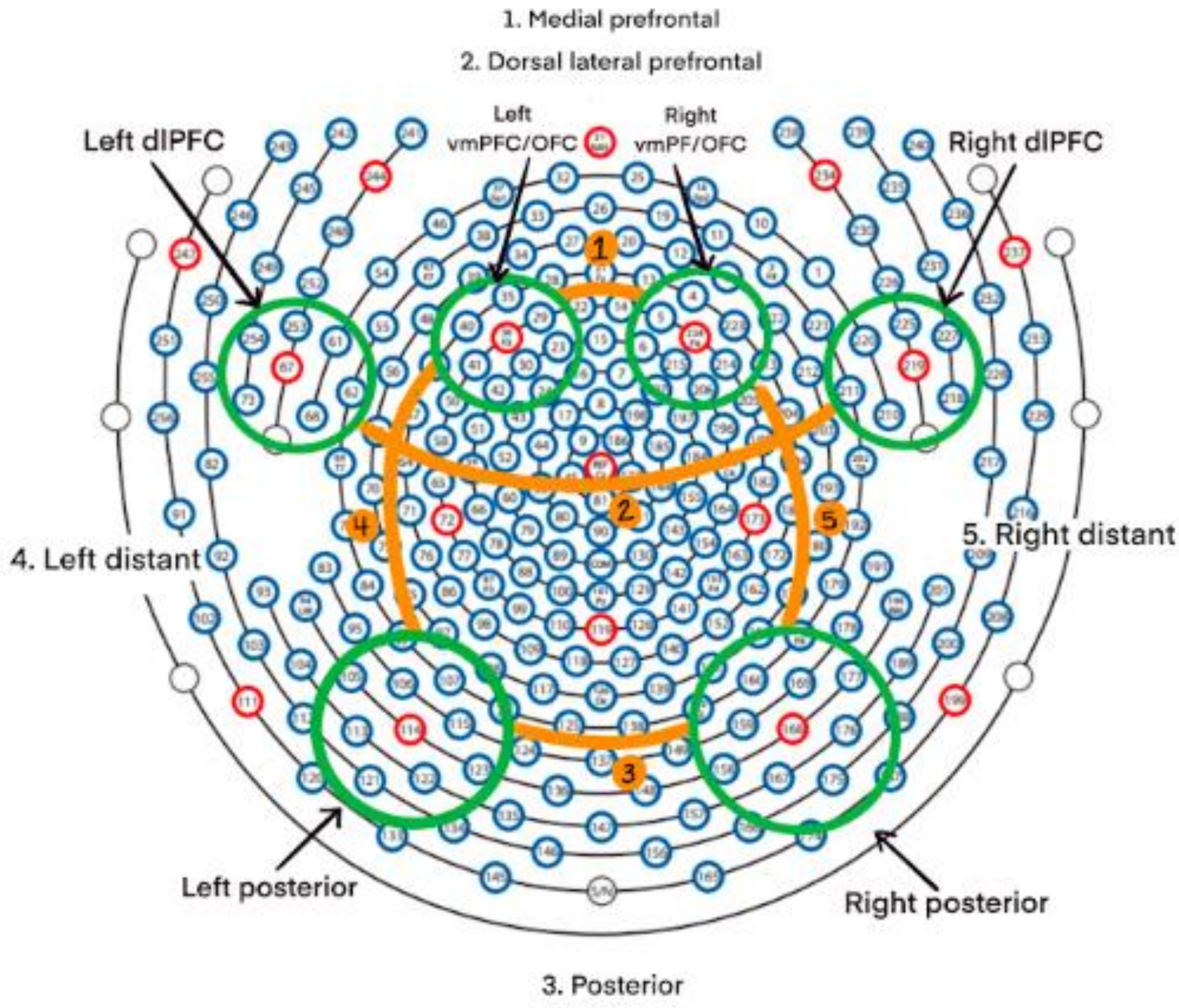

Fig 6. A map of channels included in the 256 channel Geodesic EEG net used to collect data. Electrode clusters that compose each of the six brain regions of interest are circled in green. The five brain region comparisons to measure coherence are connected by an orange line and numbered.

Lastly, inter-site phase synchrony was calculated within each band using the mscohere function in MATLAB. Coherence was calculated for five brain regions comparisons: between the left and right hemisphere of the OFC/vmPFC region (medial prefrontal in Fig. 6), dlPFC (dorsal lateral prefrontal), and posterior regions, as well as synchrony between the OFC/vmPFC and posterior region of each hemisphere (left distant and right distant). Coherence can vary from 0 (random phase angle across trials) to 1 (identical phase angles across trials). For each participant, I calculated their average coherence between each of the five brain comparison regions of interest over all trials, for both epoch windows of interest (2).

To investigate the impact of stress and gender on neural activity three sets of multivariate analyses were conducted, depending on whether they involved the decision process, processing gain feedback, or processing loss feedback. Within each set, power and coherence within each of the three power bands of interest across all trials were analyzed for six brain regions (Fig 6). In each set, two-way MANOVAs were conducted for each brain region, with gender (male or female) and stress condition (stress or no stress) as the independent variables and average power across each power band (theta, beta, and gamma) serving as the three dependent variables.

Multivariate Analyses Set 1: Decision Process

For the first set, examining all trials during the decision making period (before and immediately after a response is made), there were no significant interactions or main effects found for gender or stress condition on average power within any frequency band or brain region investigated (Appendix E).

However, the first set of analyses *did* reveal gender effects when investigating coherence, or synchrony, between brain regions. For each of the five brain region comparisons, two-way MANOVAs were conducted with gender (male or female) and stress condition (stress or no stress) and average coherence across each power band (theta, beta, and gamma) serving as the three dependent variables. First, although there was no significant interaction between gender and stress (F(1,63) = 0.885, p=.454) on coherence between the dorsal lateral prefrontal regions, or main effect of stress (0.713, p=.548), there was a significant main effect of gender (10.764, p<.001). The average coherence was greater for males as compared to females, and this relationship did not depend on whether the participant was under stress (Figure 7). A follow up comparison of between-subjects effects revealed significance within the theta (28.244, p<.001), beta (21.251, p<.001) and gamma (19.046, p<.001) bands. These results suggest that males show greater coherence between the left and right dlPFC regions during the decision making process as compared to females.

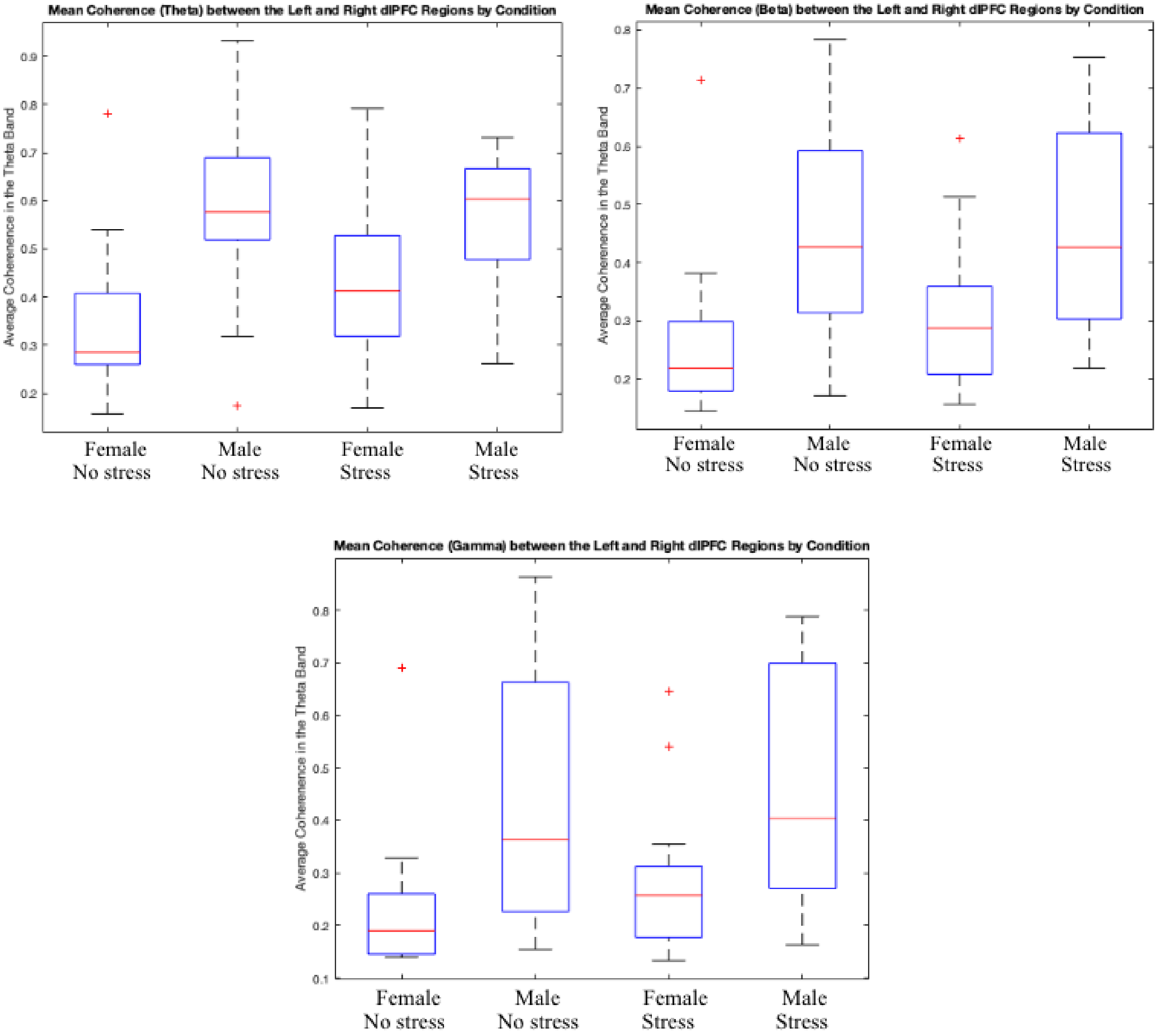

Fig 7 Average coherence between the left and right dlPFC (dorsal lateral prefrontal) regions within the theta (upper left), beta (upper right) and gamma (bottom) bands during the decision process, categorized by stress condition and gender. There was a significant main effect of gender.

When focusing on coherence between the left and right posterior regions there was also no significant interaction between gender and stress (F(1,63) = 1.446, p=.238) on coherence, or main effect of stress (0.686, p=.564). However, there was a significant main effect of gender (7.042, p<.001).). Looking at Figure 8, it appears as though females displayed greater coherence between posterior regions, but a follow up of comparisons of between-subjects effects did not reveal significance at any of the three power bands. This suggests that the relationship between gender and coherence between these regions is a combined effect of all three power bands that involves some interaction or covariation across the three, rather than being driven by a straightforward relationship in any particular band.

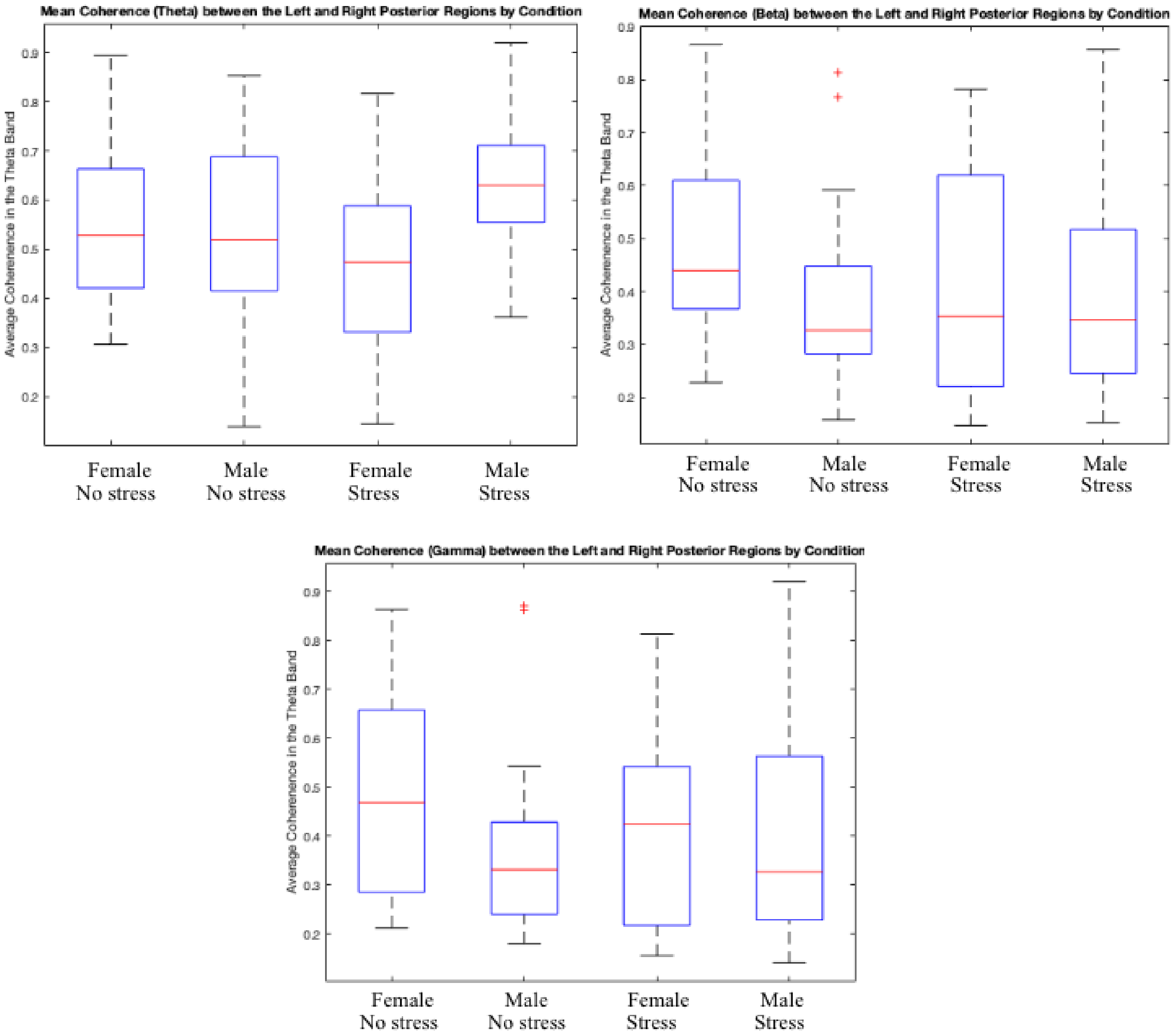

Fig 8 Average coherence between the left and right posterior regions within the theta (upper left), beta (upper right) and gamma (bottom) bands during the decision process, categorized by stress condition and gender. There was a significant main effect of gender.

Gender also revealed a significant main effect on average coherence between the right distant regions (F(1,63)=3.349, p=.024). Specifically, females showed greater average coherence as compared to males within the beta and gamma band (Fig 9). A similar trend was seen in the theta band, except males under stress displayed the greatest average coherence compared to all other conditions (Fig. 9). A follow up comparison of between-subjects effects did not reveal significance at any of the three power bands. There was no main effect of stress (1.308, p=.280) or interaction between gender and stress (0.760, p=.521).

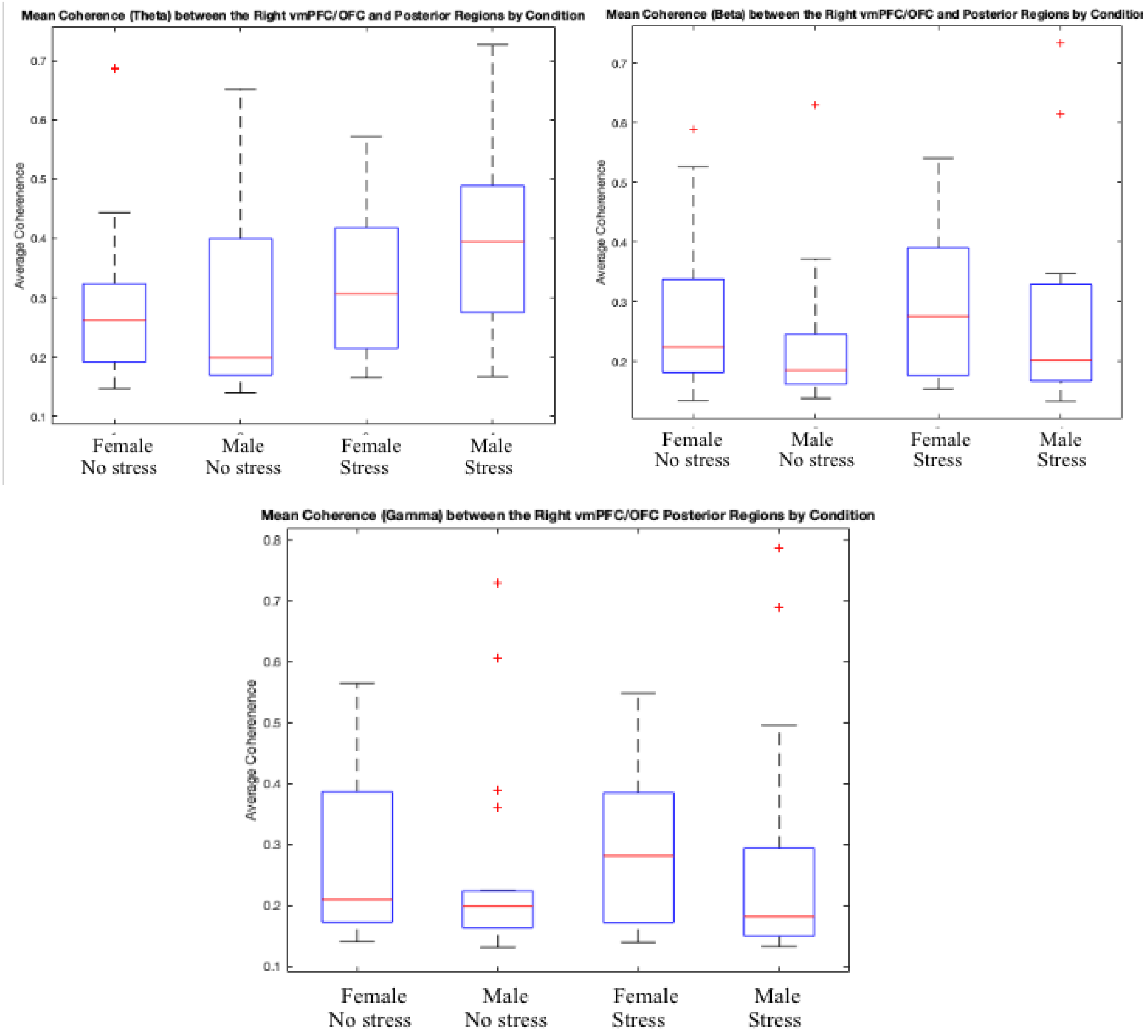

Fig 9 Average coherence between the right vmPFC/OFC and right posterior (right distant) regions within the theta (upper left), beta (upper right) and gamma (bottom) bands during the decision process, categorized by stress condition and gender. There was a significant main effect of gender.

In addition, gender revealed a significant main effect on average coherence between the left distant regions (F(1,63)=4.678, p=.005) and interaction between gender and stress (2.751, p=.050). Females appeared to show greater coherence between these frontal and posterior regions as compared to men (Fig. 10), but this relationship depended on whether the person is under stress. Males appear to display greater coherence when making decisions under stress whereas women appear to display lower coherence when making risky decisions under stress. In a follow up comparison of between-subjects effects the only band to reveal significance was the theta band within the interaction between gender and stress (6.200, p=.015). There was no main effect of stress on coherence between the left vmPFC/OFC and left posterior regions (1.459, p=.234).

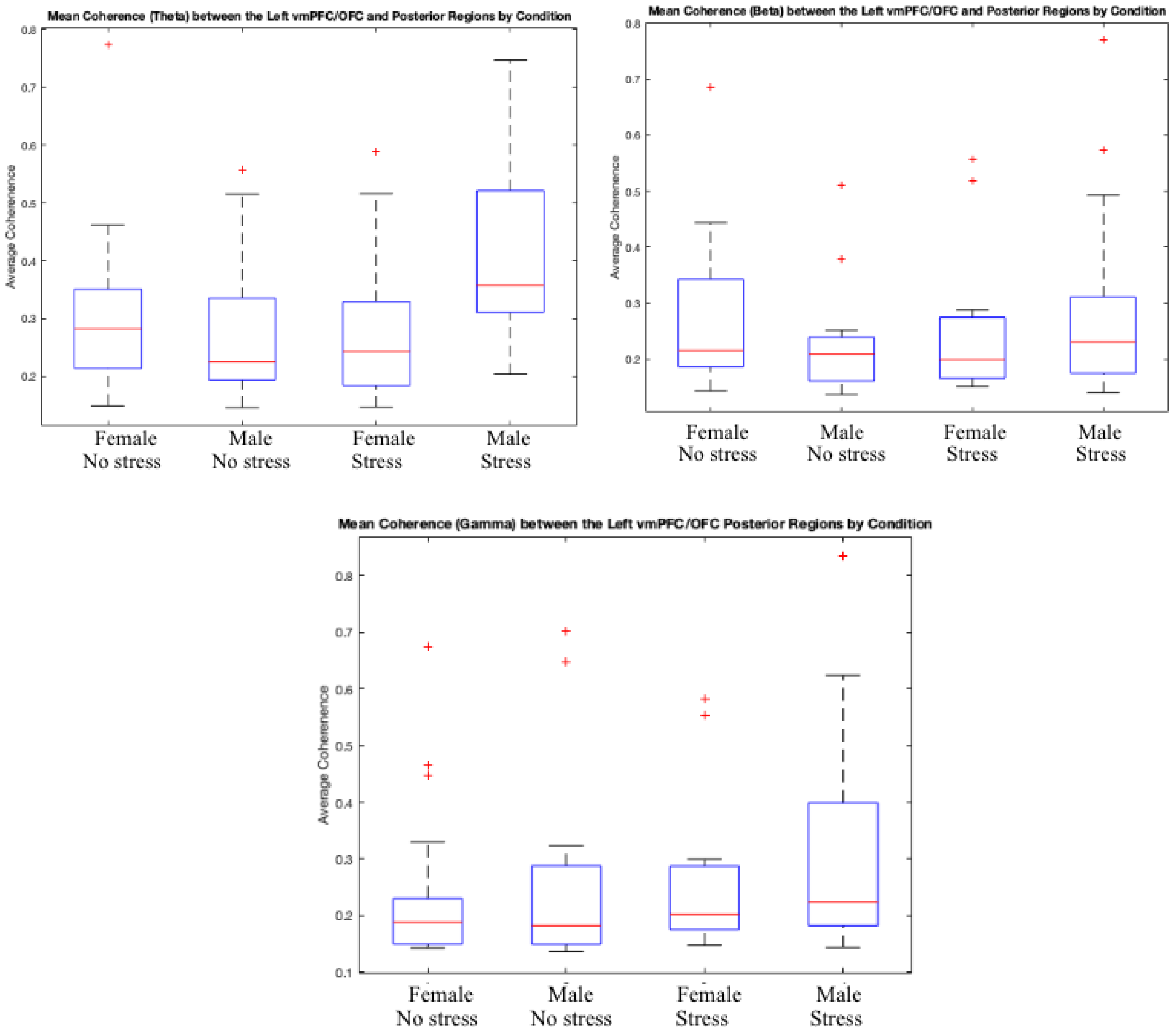

Fig 10 Average coherence between the left vmPFC/OFC and left posterior (left distant) regions within the theta (upper left), beta (upper right) and gamma (bottom) bands during the decision process, categorized by stress condition and gender. There was a significant main effect of gender and a significant interaction between gender and stress.

Lastly, for the set of analyses examining the decision process, there were no significant relationships found between gender and stress on the coherence between the right vmPFC/OFC and right posterior regions (Appendix F).

Multivariate Analyses Set 2: Processing Gain Feedback

To investigate the impact of stress and gender on neural activity while processing gain feedback (900-3000ms after a response was made), another set of two-way MANOVAs were conducted. Within this set, power and coherence within each of the three power bands of interest across all trials were analyzed for six brain regions (Fig 6). Again, gender (male or female) and stress condition (stress or no stress) as the independent variables and average power across each power band (theta, beta, and gamma) serving as the three dependent variables. To explore whether net score, or performance on the IGT, explained any of the relationships between gender and stress on neural activity all ANOVAs were repeated with net score as a covariate.

I will again focus on power first. Although there was no significant interaction between gender and stress (F(1,63) = 2.054, p=.115) on average power within the left vmPFC/OFC region in response to receiving a gain, or main effect of gender (0.2.684, p=.054) there was a significant main effect of stress condition (3.251, p<.027). On average, over all three bands the stress condition resulted in greater power (theta M=17.858, SE=7.669; beta M=7.809, SE=5.103; gamma M=6.329, SE=4.200) as compared to the no stress condition (theta M= 3.538 SE=7.669; beta M=0.341, SE=4.738; gamma M=0.158, SE=3.900). However, a follow up comparison in a test of between-subjects effects revealed this comparison to be insignificant within all bands.

When net score was added as a covariate this main effect of stress was still found (3.063, p=.035).

Focusing on average power within the right dlPFC region next, there was no significant interaction between gender and stress (F(1,63) = 2.375, p=.078) but there was a significant main effect of gender (3.601, p=.018). When looking at average power within each band, females appeared to have higher average power (theta M= M=14.565, SE=7.838; beta M=7.234, SE=4.737; gamma M=5.811, SE=3.886) than males (theta M=9.469, SE=8.005; beta M=0.811, SD=4.838; gamma M=0.515, SD=3.969). A follow up comparison in a test of between-subjects effects revealed this comparison to be insignificant within all bands. There was also a main effect of stress (2.908, p=.041), but again, a follow up of comparisons revealed insignificance within all three power bands. On average the stress condition on higher power within all three bands (theta M=19.714, SE=8.210; beta M=7.663, SE=4.962; gamma M=6.151, SE=4.701) as compared to the no stress condition (theta M=4.320, SE=7.623; beta M=0.382, SE=4.607; gamma M=0.174, SE=3.780). When net score was added as a covariate the main effect of gender remained significant (3.363, p=.024), however the main effect of stress disappeared (2.692, p=.054).

Shifting to the opposite hemisphere, to the left dlPFC region, there was again no interaction between stress and gender (F(1,63) = 1.839, p=.149) on average power within each of the three bands, or main effect of stress (1.707, p=.174) in response to receiving a positive outcome. However, there was again a main effect of gender (6.053, p=.001). Females showed greater power within the theta band (M=17.832, SE=10.205) as compared to males (M=15.490, SE=10.422). This pattern was also seen in the beta band (female M=9.286, SE=6.121; male M=1.020, SE=6.251) and the gamma band (female M=7.466, SE=5.003; male M=0.627, SE=5.110). A follow up comparison in a test of between-subjects effects revealed this comparison to be insignificant within all bands. Adding net score as a covariate did not impact whether the main effect of gender was significant (5.730, p=.002).

Three brain regions did not show any relationship between their average power in response to receiving a gain and gender or stress. Those regions were the right vmPFC/OFC and left and right posterior regions. The results of their ANOVAs can be found in Appendix G.

The second set of analyses that focused on processing feedback in response to a gain also revealed significant effects when investigating coherence, or synchrony, between brain regions. For each of the five brain region comparisons, two-way MANOVAs were conducted with gender (male or female) and stress condition (stress or no stress) and average coherence across each power band (theta, beta, and gamma) serving as the three dependent variables.

Focusing on average coherence between the medial prefrontal regions when the outcome resulted in a gain, there was no significant interaction between gender and stress (F(1,63) = 1.161, p= .332), or main effect of stress (2.236, p=.093). However, there was a main effect of gender (3.797, p=.014). Overall, males had greater average coherence between the left and right hemispheres of the vmPFC/OFC regions within all three bands (theta M=0.341, SE=0.022; beta M=0.277, SE=0.022; gamma M=0.317, SE=0.027) as compared to females (theta M= 0.251, SE=0.022; beta M=0.225, SE=0.022; gamma M=0.241, SE=0.027). A follow up comparison of between-subjects effects revealed significance only within the theta band (8.115, p=.006). The main effect of gender remained significant when net score was added as a covariate (3.542, p=.020).

There was also a main effect of gender found on coherence between the dorsal lateral prefrontal regions (F(1,63) = 13.285, p<.001). Looking at Figure 11, it appears that across all bands males had greater coherence between the left and right dlPFC regions while receiving a gain during the feedback time period as compared to females. A follow up comparison of between-subjects effects revealed significance within the theta (38.694, p<.001), beta (23.650, p<.001) and gamma (20.298, p<.001) bands. However, there was no main effect of stress (.588, p=.625) or interaction between stress and gender (.238, p=.869). The main effect of gender remained significant when net score was added as a covariate (14.101, p<.001).

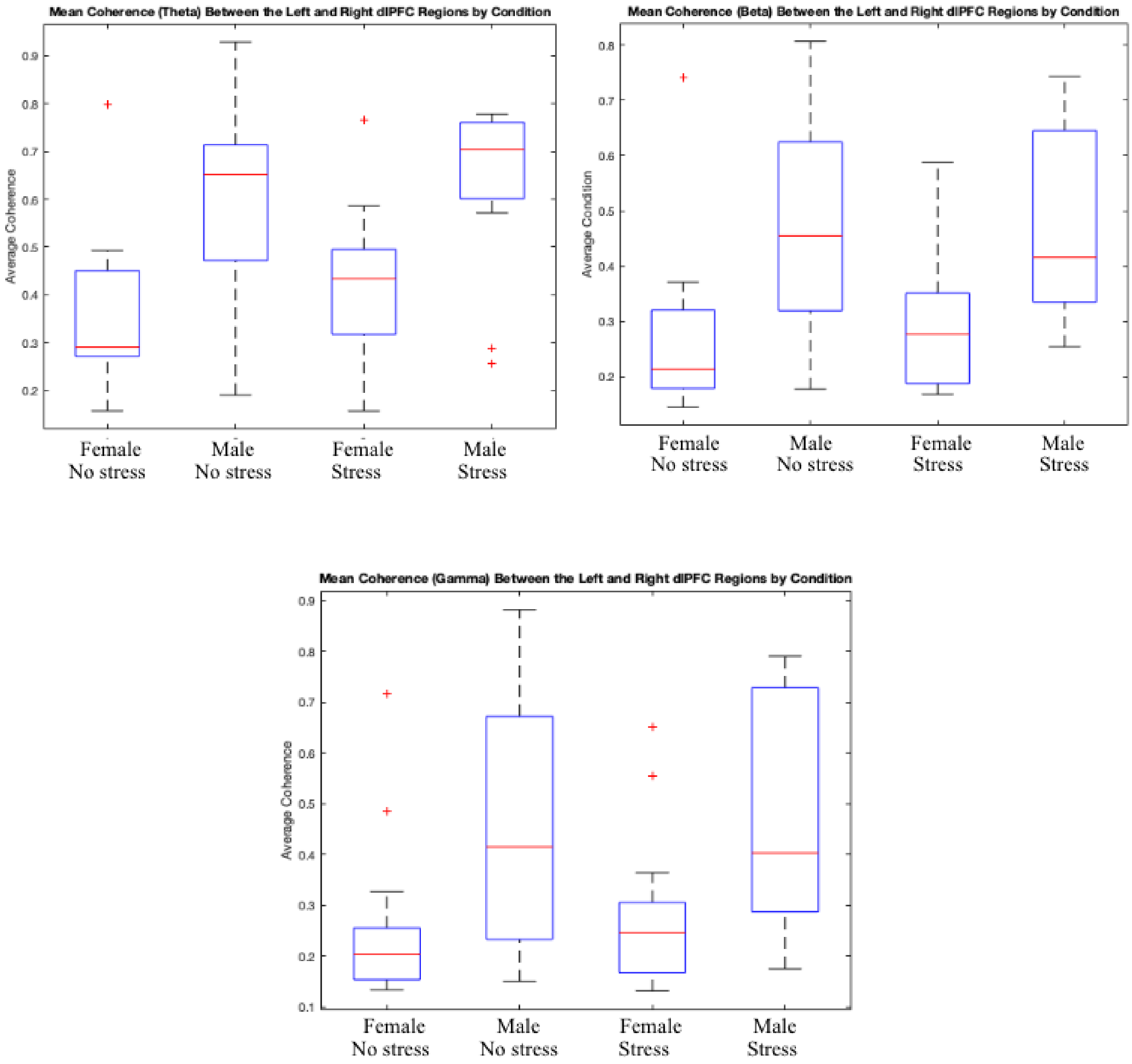

Fig 11 Average coherence between the left and right dlPFC (dorsal lateral prefrontal) regions within the theta (upper left), beta (upper right) and gamma (bottom) bands during the feedback timeframe for trials that results in a gain, categorized by stress condition and gender. There was a significant main effect of gender.

Turning to average coherence between the left and right posterior regions when the outcome resulted in a gain, there was no significant interaction between gender and stress (F(1,63) = 1.317, p= .277), or main effect of stress (1.035, p=.383). However, there was again a main effect of gender (7.167, p<.001). Looking at Figure 12, it appears as though males on average had a higher coherence between the left and right posterior regions within the theta and gamma bands as compared to females. A follow up comparison of between-subjects effects did not reveal significance within any of the bands. However, within the beta band females in the no stress condition appear to have higher coherence than the three other conditions. The main effect of gender remained significant when net score was added as a covariate (7.404, p<.001).

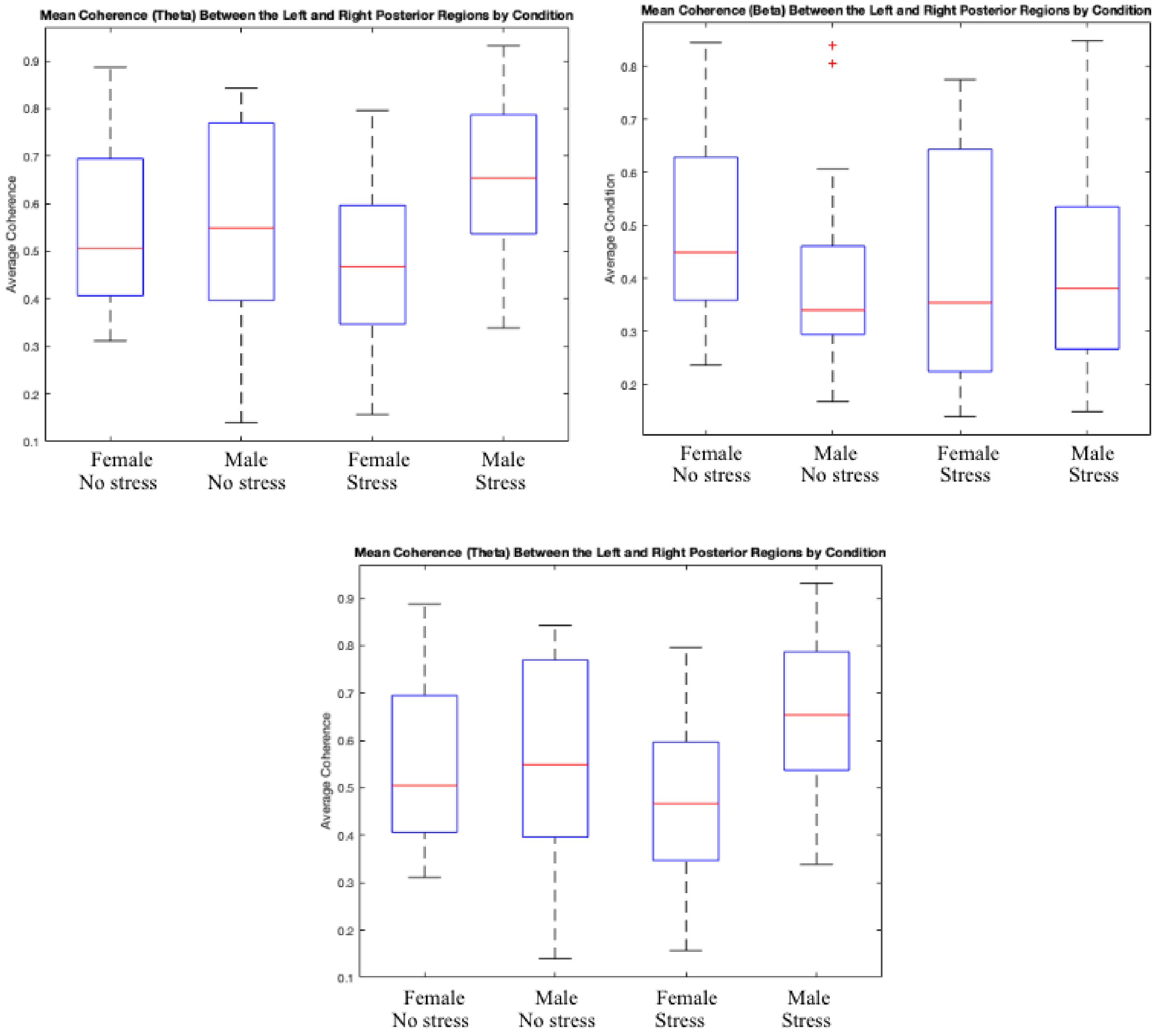

Fig 12 Average coherence between the left and right posterior regions within the theta (upper left), beta (upper right) and gamma (bottom) bands during the feedback timeframe for trials that results in a gain, categorized by stress condition and gender. There was a significant main effect of gender.

Lastly, there was another main effect of gender on coherence between the left distant regions (F(1,63)= 5.165, p=.003). A follow up comparison of between-subjects effects did not reveal significance within any of the bands. When looking at Figure 13, it appears as though males showed greater coherence between the left vmPFC/OFC and posterior regions as compared to females. There was no significant main effect of stress (1.282, p=.288) or interaction between gender and stress (2.542, p=.072) found. When net score was added as a covariate the main effect of gender remained significant (5.141, p=.003). There were no significant relationships found when investigating coherence between the right distant regions (Appendix H).

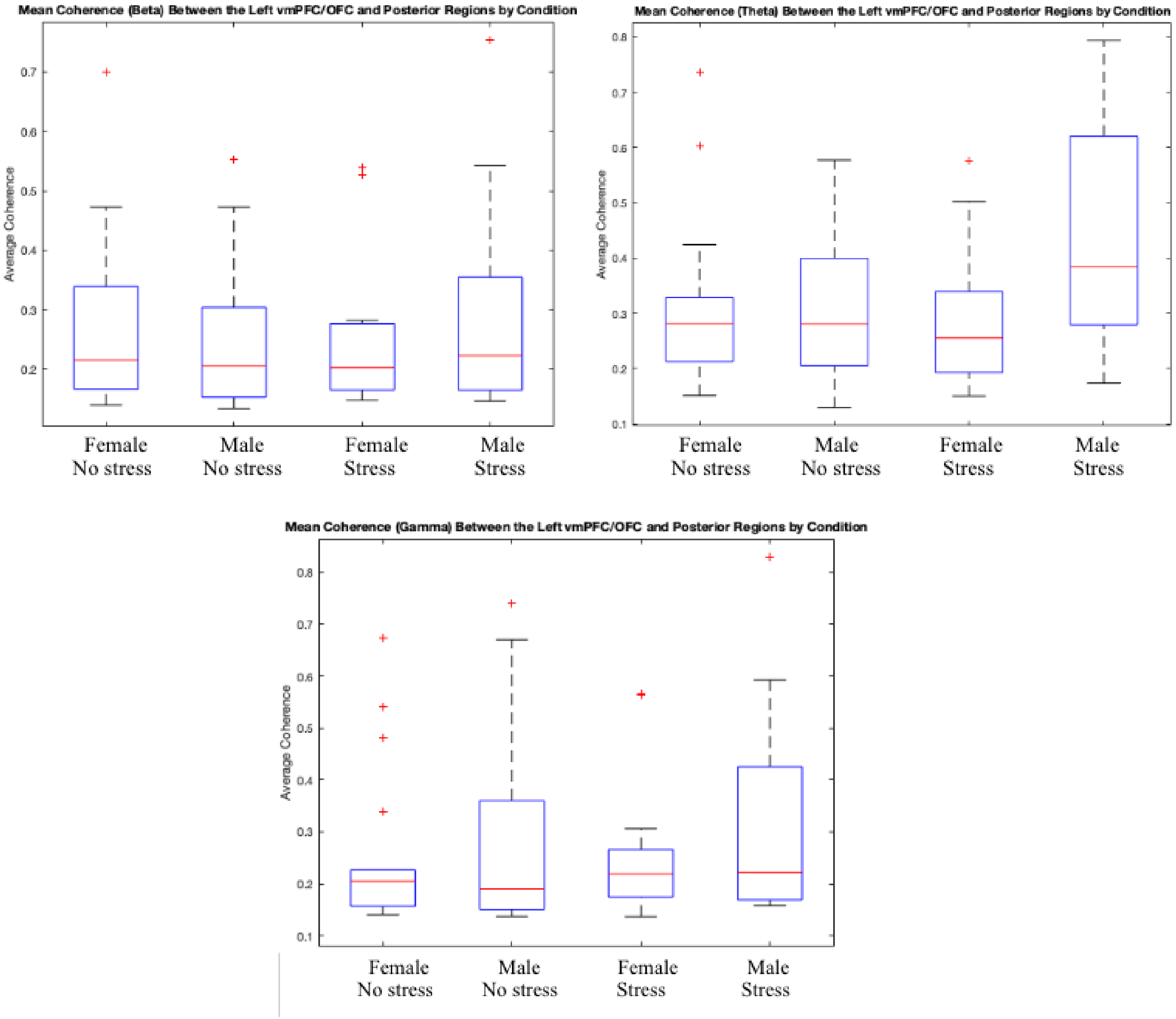

Fig 13 Average coherence between the left vmPFC/OFC and posterior (left distant) regions within the theta (upper left), beta (upper right) and gamma (bottom) bands during the feedback timeframe for trials that results in a gain, categorized by stress condition and gender. There was a significant main effect of gender.

Multivariate Analyses Set 3: Processing Loss Feedback

The third and final set of MANOVAS investigated the impact of stress and gender on neural activity while processing loss feedback (900-3000ms after a response was made). Just as with the last sets, power and coherence within each of the three power bands of interest across all trials were analyzed for six brain regions (Fig 6). Again, gender (male or female) and stress condition (stress or no stress) as the independent variables and average power across each power band (theta, beta, and gamma) serving as the three dependent variables. To explore whether net score, or performance on the IGT, explained any of the relationships between gender and stress on neural activity all ANOVAs were repeated with net score as a covariate.

I will again focus on power first. Within the right dlPFC region in response to receiving a loss there were a few relationships found between gender and stress. First, there was a significant interaction between gender and stress (F(1,63) = 3.080, p= .034), a significant main effect of stress (2.784, p=.048) and a significant main effect of gender (3.851, p=.014). Within all three bands, females had higher average power in the right dlPFC region while receiving a negative outcome (theta M=19.561, SE=11.648; beta M=11.605, SE=7.545; gamma M=9.083, SE=5.950) as compared to males (theta M=8.337, SE=11.940; beta M=0.713, SE=7.734; gamma M=0.488, SE=6.099). In addition, there was a higher average power within all three bands in this region when participants were in the stress condition (theta M=25.120, SE= 12.046; beta M=11.984, SE=8.036; gamma M=9.381, SE=6.337) as compared to the no stress condition (theta M=2.768, SE=11.150; beta M=0.334, SE=7.223; gamma M=0.190, SE=5.696). A follow up comparison of between-subjects effects did not reveal significance within any of the bands. All effects remained significant when net score was added as a covariate.

There was also a main effect of gender on average power in the opposite hemisphere, within the left dlPFC region in response to receiving a loss (F(1,63)=4.170, p=.009). However, there was no main effect of stress (1.831, p=.151) or interaction between gender and stress (3.000, p=.233). When looking at average amplitude within each band, females appeared to have higher average power within the theta band (M=24.757, SD=17.113) as compared to males (M=23.828, SD=17.543). This pattern is also seen in the beta band (female M=14.944, AD=9.756; male M=1.396, SD=10.001) and the gamma band (female M=11.672, SD =7.663; male M=0.650, SD=7.856). Again, a follow up comparison of between-subjects effects did not reveal significance within any of the bands. The main effect of gender remained significant when net score was added as a covariate (3.931, p=.013).

There were no significant relationship found between gender and stress and average power within any of the other brain regions (left and right vmPFC/OFC regions and left and right posterior regions) when receiving a loss during the feedback time period (Appendix I).

The third set of analyses, focusing on processing feedback in response to a loss, also revealed significant effects when investigating coherence, or synchrony, between brain regions. For each of the five brain region comparisons, two-way MANOVAs were conducted with gender (male or female) and stress condition (stress or no stress) and average coherence across each power band (theta, beta, and gamma) serving as the three dependent variables.

A couple main effect of gender were found when focusing on coherence in response to a loss. First, average coherence between the dorsal lateral prefrontal regions resulted in no significant interaction between gender and stress (F(1,63) = 0.131, p= .941), or main effect of stress (1.057, p=.374). However, there was a main effect of gender (11.482 p<.001). In all bands, males showed greater average coherence between the left and right dlPFC region (theta M=0.618, SE=.028; beta M=0.476, SE=.027; gamma M=0.461, SE=.033) as compared to females (theta M=0.404, SE=.028; beta M=0.285, SE=.027; gamma M=0.262, SE=.032). A follow up comparison of between-subjects effects revealed significance within the theta band (.758, p<.001), the beta band, (.601, p<.001) and the gamma band (.657, p<.001). The main effect of gender remained significant when net score was added as a covariate (11.994, p<.001).

Next, when looking at average coherence between the left and right posterior regions when the outcome resulted in a loss, there was also no significant interaction between gender and stress (F(1,63) = 0.759, p= .521), or main effect of stress (1.224, p=.309). But, again, there was a main effect of gender (6.310, p=.001). A follow up comparison of between-subjects effects revealed significance only within the theta band (4.051, p=.048), where males had greater average coherence (M=0.615, SE=.032) then females (M=0.526, SE=.031). The main effect of gender remained significant when net score was added as a covariate (6.214, p=.001).

Two different brain region comparisons found a main effect of stress. Focusing on average coherence between the medial prefrontal regions when the outcome resulted in a loss, there was no significant interaction between gender and stress (F(1,63) = 2.455, p= .072), or main effect of gender (2.300, p=.086). On average the stress condition revealed greater coherence between the left and right vmPFC/OFC regions (theta M=0.355, SE=.024; beta M=0.271, SE=.023; gamma M=0.284, SE=.028) as compared to the no stress condition (theta M=0.246, SE=.022; beta M=0.230, SE=.020; gamma M=0.266, SE=.025). However, there was a main effect of stress (4.051, p=.011). A follow up comparison of between-subjects effects revealed significance only within the theta band (11.124, p=.001). The main effect of stress remained significant when net score was added as a covariate (3.897, p=.013).

Turning to average coherence between the right distant regions when the outcome resulted in a loss, there was no significant interaction between gender and stress (F(1,63) = 1.877, p= .143), or main effect of gender (1.872, p=.144). However, there was a main effect of stress (3.270, p=.027). Again, on average the stress condition revealed greater coherence between the right vmPFC/OFC and right posterior regions (theta M=0.403, SE=.027; beta M=0.291, SE=.024; gamma M=0.284, SE=.028) as compared to the no stress condition (theta M=0.292, SE=.024; beta M=0.247, SE=.0202 gamma M=0.261, SE=.025). A follow up comparison of between-subjects effects revealed significance only within the theta band (9.332, p=.003). The main effect of stress remained significant when net score was added as a covariate (3.108, p=.033).

Lastly, only one brain region showed an interaction between stress and gender. When focusing on the left distant regions when the outcome resulted in a loss there was a significant interactions between gender and stress (F(1,63)=3.095, p=.033). Looking at Figure 14, it appears as though males under stress display greater coherence between the frontal and posterior regions in the left hemisphere as compared to males that are not under stress, whereas females show greater coherence when they are not under stress as opposed to when they are. A follow up comparison of between-subjects effects revealed significance only within the theta band (5.843, p=.019), which is revealed in Figure 14. There was no main effect of stress (1.075, p=.367) or gender (1.653, p=.187) on average coherence between the left vmPFC and posterior regions in response to a loss. The interaction between gender and stress remained significant when net score was added as a covariate (3.077, p=.034).

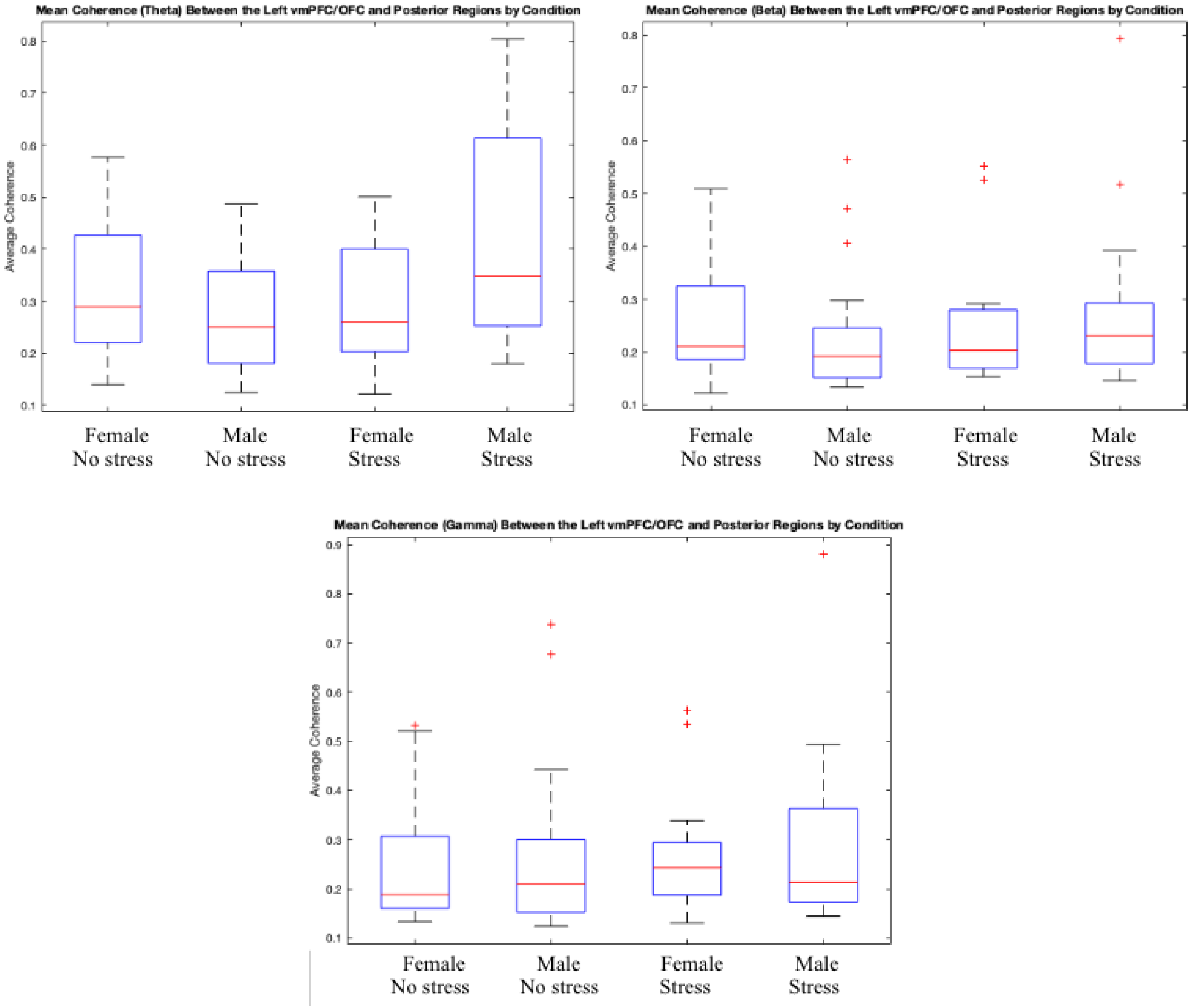

Fig 14 Average coherence between the left vmPFC/OFC and posterior (left distant) regions within the theta (upper left), beta (upper right) and gamma (bottom) bands during the feedback timeframe for trials that results in a loss, categorized by stress condition and gender. There was a significant interaction between gender and stress, specifically within the theta band.

There were a large number of neural analyses run with an exciting number of significant effects found, making it difficult to identify a pattern when presented one after another as they were in the results above. I have provided two tables to help assist. Table 2 gives a summary of the different gender effects found during the decision process, while processing gain feedback, or loss feedback, when focusing on average power or coherence between brain regions. All results included in Table 2 and 3 are significant effects found from the three sets of multivariate analyses. Overall, while processing both types of feedback, it appears that males show greater coherence between brain regions as compared to females. However, during the decision making process time period females showed greater coherence between hemispheres in the posterior regions and the medial prefrontal regions, whereas males showed greater coherence between dorsal lateral prefrontal.

Table 2
Main Effects of Gender

Decision Process		
Power/Coherence value	Brain Region/s	Gender with higher
Coherence	Right & Left dlPFC	males
Coherence	Right & Left Posterior	females
Coherence	Right & Left vmPFC/OFC	females
Processing Gain Feedback		
Power	Right dlPFC	females
Power	Left dlPFC	females
Coherence	Right & Left dlPFC	males
Coherence	Right & Left vmPFC/OFC	males
Coherence	Right & Left Posterior	males
Coherence	Left vmPFC/OFC & Posterior	males
Processing Loss Feedback		
Power	Right dlPFC	females
Power	Left dlPFC	females
Coherence	Right & Left dlPFC	males
Coherence	Right & Left Posterior	males

Table 3 gives a summary of the main effects of stress, where it is clear that stress increased coherence and power, but only in certain brain regions. Other brain regions failed to find significance, but it was never the case that the no stress condition produced greater activity or coherence.

There were only two instances in which an interaction was found between stress and gender, both when investigating coherence between the left frontal (vmPFC/OFC) and left posterior regions. During the decision process and while processing gloss feedback males displayed greater coherence when placed under stress as compared to their non-stressed counterparts, as opposed to females who showed greater coherence in the no-stress condition as compared to the stress condition.

Table 3
Main Effects of Stress

Processing Gain Feedback		
Power/Coherence	Brain Region/s	Condition with higher value
Power	Right dlPFC	stress
Power	Left vmPFC/OFC	stress
Processing Loss Feedback		
Power	Right dlPFC	stress
Coherence	Left & Right vmPFC/OFC	stress
Coherence	Right vmPFC/OFC & Posterior	stress

Discussion

Understanding the fluctuation in cognitive processes involved in decision making under conditions of stress is important to predict the choices of individuals in careers with important responsibilities surrounding human lives, policy, and finance. It's also necessary to understand individual differences in response to stress that may be related to gender or even general decision making styles. The current project aimed to use a combination of behavioral and neural data to investigate these questions. The following discussion will be structured in a flow similar to the previous sections, focusing first on the behavioral findings and how they compare to existing literature, then the computational modeling results, and ending with the neural results while elaborating on the relationship found between each.

First, the lack of significance found for the stress manipulation check was disappointing but admittedly unsurprising. Past studies have also reported difficulty finding a difference in subjective stress ratings between control and stress conditions, especially in male participants (Reschke-Hernandez, Okerstrom, Edwards & Tranel, 2017). In the current study all participants filled out their subjective stress rating in front of the experimenter, which may have provided a possible confound. People may not be as willing to admit they are stressed when another person is watching. Especially if that other person is of the opposite gender (as was the case with male participants). However, during the debrief those in the stress condition verbally expressed relief at not having to repeat the CPT and made comments about how cold and uncomfortable the water was. In addition, significant differences between the stress and no stress condition were still found within the behavioral and neural data. This information leads me to believe that the stress induction was indeed successful, even if participants were not willing to admit it through self-report. Future studies should ensure properly functioning heart rate equipment and/or data collection protocol to circumnavigate this issue.

Results from the behavioral data were mixed. Overall, participants in this sample performed slightly worse than the average sample of college-aged students according to their net score. In most experiments participants complete the IGT with a positive score hovering around 10 (Ligneul, 2019; Bechara et all 1997, 1999). However, participants in the stress condition in the current sample received an average net score a few points above zero, and in the no stress condition scored at or just below zero. Other studies have reported stress and/or anxiety to negatively impact IGT score depending on gender (De Pascalis et al., 2012), so it is interesting to note that on average both gender are performing better, though insignificantly, under stress in the current study. Other studies have reported that on average males outperform females on the IGT (Bruine de Bruin et al., 2007) but results from this study add to the literature that fails to find support for this claim (Bolla et al., 2004).

Win-stay and lose-shift were two strategies quantified by the toolbox used. Participants in this sample produced average win-stay and lost-shift scores in line with those in other studies (Ligneul,2019). I predicted that the win-stay and lose-shift variables would be affected by stress condition, but not gender. Specifically, I hypothesized that on average individuals in the stress condition would have higher win-stay and lose-shift scores than individuals in the no stress condition. This was motivated by previous studies that found individuals under stress were more likely to use simpler, less cognitively demanding strategies (Yang, Aloe & Feely, 2014). For example, people under stress were more likely to use a compensatory strategy than when they were not under stress (Starke et al., 2008). However, the results from the current analyses did not support my prediction, instead finding no difference in the use of win-stay or lose-shift strategies between conditions. This may be driven by the possibility that these two strategies are more complicated and cognitively demanding than simpler strategies participants are using to complete the task but were not quantified.

Next, the computational modeling comparison resulted in the VSE model as the best performing model, consistent with past papers (Ligneul, 2019; Pettit & Johnson, under review). Compared to other healthy, college-age populations this sample yielded similar mean best fit inverse decay, sensitivity, explore learning rate, and choice consistency parameter values (Ligneul, 2019). However, the mean best fit exploration bonus parameter of this sample (0.09) was lower than other young adults included in Ligneul (2019)'s sample which hovered near 1. This suggests that compared to other samples, on average these participants were less attracted to decks that had not been recently explored. When focusing on the effects of stress and gender differences in parameter values only one parameter showed a significant relationship: the explore alpha parameter. There was a significant interaction between gender and stress on the explore alpha parameter, used to control how quickly a participants' inclination to explore available decks rather than exploit a familiar one grows. The results suggest that, compared to men who are not under stress, males that are placed in a stressful situation are slower to build an inclination to explore options that haven't been chosen recently. On the other hand, females under stress will more quickly build an inclination to explore options that haven't been chosen recently as compared to those who are not under stress.

It is interesting to note that even though participants’ overall performance was not impacted by stress or gender, the strategy used to compensate for the cognitive impacts of stress and achieve similar levels of performance, were different depending on gender.

There were a few significant relationships found between behavioral data and computational modeling parameters. First, the positive correlation between net score and participants’ best fit inverse decay parameter suggested that individuals who perform better on the IGT are likely to exhibit greater learning rates, or integration of past experiences into their current decision. This is validation for theoretical interpretation of the inverse decay parameter, used to represent the cognitive process of learning. Naturally, better learners are likely to end up with higher scores. There was also a negative correlation between participants’ win-stay score and their explore bonus parameter, meaning that individuals who more often used the strategy of sticking with a deck after it produces a positive outcome are less likely to explore all four available options and more likely to continue choosing a familiar deck. Again, this relationship is reasonable considering the win-stay strategy requires repeated exploitation of a deck when it continues to produce a gain and the explore bonus parameter is meant to represent a person’s tendency to exploit or explore available options. The same logic can be applied to explain the positive correlation between the explore bonus parameter and lose-shift scores which suggests that participants who more often use the strategy of shifting away from a deck after it produces a negative outcome are more likely to explore all four decks available rather than exploiting one. Lastly, lose-shift scores also had a positive relationship with the choice constancy parameter suggesting that individuals who use the strategy of switching away from it deck when it doles a loss have a more deterministic choice policy.

To date, few studies have explored the relationship between individual differences and computational model parameters. Although not a primary goal of this project, it was exciting to find a few relationships between the two that again provide support for the theoretical framework used by the VSE model and the cognitive processes it contains. First, venturesomeness scores showed a predictable, positive correlation with participants' value sensitivity parameters. This means that individuals with a high willingness to take on risk or embark on new experiences are more likely to prefer options that produce large outcomes more frequently over those that produce small, frequent outcomes. In addition, the choice consistency parameter showed a positive relationship with participants' personal control scores suggesting that individuals who feel a greater need for control over their personal life and actions are also more likely to make decisions consistent with the expected values they have so far experienced. Again, this is a logical relationship when considering the lack of control one feels when placed in an inconsistent, unpredictable environment. Decision consistency may be one way to foster feelings of personal control.

Finally I will focus on results from the neural data. Two different time periods during each decision were examined. The first was the decision making process time period, just before and after a response was made, but prior to receiving feedback on that outcome. Previous studies found that when a person is under stress, activity within the OFC has been shown to decrease (Pruessner et al., 2008) while activity in the dlPFC has been shown to increase (Pruessner, 2004). Based off these results, I predicted the stress condition would result in lower power within the OFC/vmPFC regions but increased power in the dlPFC region. However, this relationship was not found. In fact, there were no significant relationships found on the impact of stress on neural activity during the decision making process as measured by power in any of the six brain regions of interest. In addition, gender did not appear to have any impact on power during the decision making process. Neuroimaging studies have reported greater activation in the dlPFC during the IGT for women as compared to men (Bolla et al., 2004) and that men (not women) with damaged right prefrontal areas displayed worse performance than their neurally intact male peers (van den Bos et al., 2013). These studies motivated my prediction that women would display greater power in the dlPFC region compared to men. But as mentioned, the results of the current study did not support these predictions.

Instead, an impact of gender and stress were found within coherence between different brain regions during the decision process. First, within the dlPFC regions men showed greater coherence between the left and right hemispheres as compared to women. The dlPFC is thought to temporarily maintain currently/recently attended information (de Visser et al., 2010) such as stimulus features or location (Hunt et al., 2018) to help produce a choice. These results suggest that men use greater cross talk between regions that represent these objective stimulus property to drive decision making than women do. On the other hand, females showed greater coherence between frontal (specifically the vmPFC/OFC) and posterior regions within the right hemisphere as compared to males. Past studies have found that good performs on the IGT display increased coherence between distant brain regions, suggestion communication and allowing integrating of information that results in learning (Steriade, 2006). The vmPFC and OFC are contained in the affective loop and theorized to use salient information from the environment to assign a value to a reward/loss and outcome expectancies. Thus, women appear to show greater integration of all available information and past experiences to drive decision making as compared to men.

Most interesting, however, is the interaction found between gender and stress when focusing on coherence between frontal and posterior regions in the left hemisphere during the decision making process. Males under stress showed greater crosstalk, suggesting more integration of information, as compared to males who were not under stress. The opposite relationship was found for women, in that stress decreased the coherence seen between the left frontal and posterior regions, or their integration of information to inform decision making. Remember the interaction found within the explore alpha parameter that suggested that males under stress are slower to build an inclination to explore options that haven't been chosen recently, while females under stress will more quickly build an inclination to explore options that haven't been chosen recently. These results complement one another. If a person is not integrating all information into their decision process to make a well thought out, intentional choice, it is reasonable to assume they will build an inclination to explore options available to them.

Next, I will turn to results from the second time period during which participants received feedback, or the outcome of their choice. Because past research has found individual differences in neural activity in response to a gain as opposed to a loss, trials during this time period were separated by outcome: positive or negative. Compared to men, women showed greater power in the right and left dlPFC, regions tied to maintaining objective stimulus identities and features. This gender difference was found for trials that resulted in a loss and those that resulted in a gain. Thus, no matter the outcome, women overall showed greater activity than men in the brain region found to represent stimulus features and location (Hunt et al., 2018). However, men showed greater coherence between the left and right dlPFC in response to both a loss and to a gain as compared to women. These interesting results suggest that even though women show greater activity in the dlPFC in both hemispheres when feedback is provided, men show greater synchrony, or crosstalk between the hemispheres.

In addition, a gender difference was found in synchrony between the frontal and posterior regions in the left hemisphere. Again, when the outcome resulted in a loss or a gain, males showed greater coherence as compared to females. The increase in coherence between distant brain regions suggests that when feedback is provided males show greater integration of all available information and past experiences. It is interesting that females were the gender to show greater coherence within this hemisphere earlier in the decision, just before and after the choice was made, before the feedback was displayed. It is possible that women call upon past experiences and information when making a decision more than men do, but men integrate feedback with past experiences and information more than women do.

The last main effect of gender during the feedback time period was found in coherence between the left and right vmPFC/OFC regions in response to a gain. Overall, males had greater average coherence between the left and right hemispheres of the vmPFC/OFC regions within all three bands as compared to females. This suggests that when a gain is provided, males are displaying greater communication between the brain areas associated with using salient information from the environment to assign a value to a reward/loss and outcome expectancies.

There were also a few main effects of stress found within the neural data during the feedback time period. First, no matter whether the outcome was a gain or a loss, the stress condition resulted in greater power within the right dlPFC as compared to the no stress condition. In addition, for trials that resulted in a gain, there was greater power within the left dlPFC region during feedback in the stress condition as compared to the no stress condition. Thus, stress appears to increase activity during feedback in the right hemisphere of the brain region responsible for maintaining stimulus features and properties, but this relationship is only seen in the left hemisphere when that feedback is positive. These results in line with past studies that have reported increased activity in the dlPFC in response to stress (Preusser et al., 2004), specifically those that report right prefrontal areas to be more tightly linked to stress as compared to left areas (Starke et al., 2012).

Stress also had an impact on coherence between brain regions while participants were receiving feedback, but only when the outcome was negative. First, individuals under stressed showed greater coherence between the left and right hemisphere of the vmPFC/OFC regions as compared to those who are not under stress. Thus, stress appears to increase interhemispheric communication between the regions in the affective loop that use salient information to assign reward/loss and outcome expectancies. In addition, participants in the stress condition revealed greater intrahemispheric coherence between the right vmPFC/OFC and posterior regions, suggesting that stress may increase communication and allow integration of information with past experiences to result in learning.

Lastly, there was an interaction found between gender and stress in the opposite hemisphere, in coherence between the left vmPFC/OFC and posterior regions while receiving negative feedback. Specifically, males in the stress condition showed greater intrahemispheric synchrony between distant brain regions as compared to males in the no stress condition, whereas females under stress showed lower coherence between distant brain regions while receiving negative feedback as compared to females who were not under stress. This is the same interaction in coherence between the same brain regions that was found during the decision process time period. It is interesting to note that this relationship was not found when the outcome was positive. Therefore, placing males under stress appears to increase the crosstalk seen between distance brain regions during in response to receiving a loss and during the decision process, whereas placing women under stress appears to decrease their integration of information to inform decision making. These results support the idea that stress impacts risky decision making processes differently for men and women while in the process of deciding between options and evaluating negative feedback.

Although the results of this study are exciting and make a significant contribution to existing literature on neural activity during risky decision making this experiment does have its limitations. First, the exploratory nature of the design lacks experimental control. A stronger design would be to investigate a moderation model of stress, gender and risky decision making. Future experiments with a longer timeline and access to a large, reliable recruitment pool would benefit from this change in procedure.

Second, other brain regions have been identified to underlie the IGT including the amygdala, ventral striatum, anterior cingulate and dorsal striatum (de Visser et al., 2010). However, this proposal focuses strictly on the surface-level, frontal regions' contribution to experience-based risky decision making due to its demonstrated gender differences in activation patterns (Northoff et al., 2006) and association with stress reactions (de Visser et al., 2010). Future research should investigate how the PFC in conjunction with other brain regions underlying IGT and stress are impacted by gender differences. Also different format of IGT.

Lastly, the immense number of decisions made by the experimenter when it comes to processing EEG data opens the door to a realm of technical limitations. To begin, there a multiple "camps" when it comes to processing EEG data that make different claims about the order in which steps should be complete. It is possible that a different order of operations would result in cleaner data. In addition, the constant window required in the FFT approach is considered a limitation because high-frequency signal changes require shorter time windows to capture than those needed for low-frequency signals (Roach et al., 2008). A more flexible approach would be to use a wavelet analysis that is able to vary window size across frequencies to optimize temporal resolution of different frequencies. For example, a Morlet wavelet consists of a sine wave of a defined frequency, which is multiplied point by point to a Gaussian distribution, known as windowing. The advantage of using this method is that a wavelet demonstrates a brief oscillation rather than a sustained sine wave. This oscillation is added to a Gaussian, causing its amplitude to start at 0, then increases to a given frequency for a certain number of cycles, and returns to 0. A set of wavelets are created using this method and are passed over the data and comparisons are made between the sine waves composing the signal, allowing a small area at a time to be examined. Future analyses should consider using more flexible methods such as these.

This interdisciplinary approach combines computational modeling to allow for simulation of co-occurring cognitive processes and predictions of choice behavior, neurophysiology techniques to monitor brain activity and a complex statistical analysis to relate the parameters obtained by each modality of data. Joint modeling is a burgeoning approach in cognitive neuroscience that is unique in the way it bridges the connection between parameters of neurological and behavioral modeling (Turner, Forstmann, Love, Palmeri, & Van Maanen, 2017). Few studies have investigated EROs in relation to risky decision making in concert with parameters in computational models (De Pascalis et al., 2012), lending additional novelty to the approach used in this research proposal. This experiment provided an innovative and powerful quantitative assessment of the neurophysiological and behavioral mechanisms underlying risky decision making under stress allowing for the improvement of existing computational models of cognition.

The potential applications are varied, such as commanders simulating the likely choice behavior of different individuals under certain training protocols. For example, simulation of a computational model could predict a soldier’s poor behavioral performance under conditions of stress. Simple behavioral assessments could predetermine that the soldier has a dysfunctional increase in sensitivity to loss as represented by an inflated parameter value. The JCM approach in this proposal will allow neural data to constrain parameter values and accurately predict how the soldier will behaviorally perform tactical procedures under stress. On the other hand, this application could also be useful in clinical settings where neuroimaging data is expensive and time consuming to obtain. In order to develop treatment sensitive to the patients’ differences, clinicians must understand which brain regions are affected by the disorder. This approach aims to accomplish that need in an innovative, cost effective manner that contributes to cognitive theories of decision making.

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Appendix A

Mean directed exploration of three (DE3) or four (DE4) decks during the IGT

	No Stress		Stress	
	Male	Female	Male	Female
DE3	0.222(*.045*)	0.315(*.045*)	0.256(*.049*)	0.278(*.046*)
DE4	0.071(*.024*)	0.117(*.024*)	0.099(*.026*)	0.075(*.024*)

Mean directed exploration scores for participants in each condition (*SD*).

Appendix B

Insignificant two-way ANOVA results investigating the effect of gender and stress on participants' mean DE3 and DE4 scores.

Parameter	Interaction	Gender	Stress
DE3	0.590(*.445*)	1.508(*.224*)	0.001(*.971*)
DE4	2.049(*.157*)	0.215(*.644*)	0.078(*.781)*

A table of F-values (p-value) for DE3 and DE4 investigating the interaction between gender and stress, the main effect of gender, and the main effect of stress. All results in this table are insignificant.

Appendix C

Mean best fit VSE parameter values for each condition by gender and stress.

	No Stress		Stress	
	Male	Female	Male	Female
Inverse Decay	0.646(.*063*)	0.632(.*063*)	0.654(.*069*)	0.528(.*065*)
Sensitivity	0.295(.*046)*	0.314(.*046*)	0.390(.*050*)	0.284(.*047*)
Explore Bonus	0.317(.*586*)	0.013(.*586*)	-0.458(.*638*)	0.433(.*602*)
Choice Constancy	0.819(.*147*)	0.744(.*147*)	0.654(.*160*)	1.057(.*151*)

Mean best fit VSE parameter values for participants in each condition (*Standard Error*). Only parameters that have shown insignificant main effects of gender, stress, or an interaction between the two are shown. For the mean best fit explore alpha parameter values please refer to the results section of the manuscript.

Appendix D

Insignificant two-way ANOVA results investigating the effect of gender and stress on participants' mean best fit VSE parameter values.

Parameter	Interaction	Gender	Stress
Inverse Decay	0.747 (*.390*)	1.163(*.285*)	0.561(*.457*)
Sensitivity	1.729(*.193*)	0.859(*.357*)	0.481(*.490*)
Explore Bonus	0.980(*.326*)	0.235(*.629*)	0.086(*.770*)
Choice Constancy	2.477(*.120*)	1.176(*.282*)	0.235(*.629*)

A table of F-values (*p-value*) for each parameter investigating the interaction between gender and stress, the main effect of gender, and the main effect of stress. All results in this table are insignificant, however, the explore alpha parameter did show significance (please refer to manuscript results section).

Appendix E

Insignificant two-way ANOVA results investigating the effect of gender and stress on participants’ average power within the three bands at each brain region during the decision making process.

Region	Interaction	Gender	Stress
Right vmPFC/OFC	1.813(*.154*)	0.340(*.796*)	2.271(*.089*)
Left vmPFC/OFC	1.202(*.316*)	0.217(*.884*)	1.642(*.189*)
Right dlPFC	1.425(*.244*)	0.593(*.622*)	1.658(*.185*)
Left dlPFC	1.265(*.294*)	2.588(*.061*)	1.568(*.206*)
Right posterior	1.572(*.205*)	1.495(*.225*)	2.089(*.111*)
Left posterior	1.864(*.145*)	0.941(*.426*)	2.189(*.098*)

A table of F-values (p-value) for multivariate analyses investigating the interaction between gender and stress, the main effect of gender, and the main effect of stress. Dependent variables include average amplitude within the theta, beta, and gamma bands during the decision making process (1s before a response is given and .8s after). All results in this table are insignificant.

Appendix F

Insignificant two-way ANOVA results investigating the effect of gender and stress on participants' average coherence between each brain comparison region within the three bands during the decision making process.

Region	Interaction	Gender	Stress
Right vmPFC/OFC & posterior	1.813(*.154*)	0.340(*.796*)	2.271(*.089*)

A table of F-values (p-value) for multivariate analyses investigating the interaction between gender and stress, the main effect of gender, and the main effect of stress. Dependent variables include average coherence within the theta, beta, and gamma bands during the decision making process (1s before a response is given and .8s after). Results in this table are insignificant.

Appendix G

Insignificant two-way ANOVA results investigating the effect of gender and stress on participants' average power within the three bands at each brain region during trials that result in a gain. Electrical activity is captured while feedback is displayed.

Region	Interaction	Gender	Stress
Right vmPFC/OFC	0.1.85(*.153*)	2.028(*.119*)	1.628(*.192*)
Right posterior	2.003(*.123*)	1.355(*.265*)	1.640(*.265)*
Left posterior	1.667(*.183*)	0.997(*.400*)	1.081(*.364)*

A table of F-values (p-value) for multivariate analyses investigating the interaction between gender and stress, the main effect of gender, and the main effect of stress. Dependent variables include average amplitude within the theta, beta, and gamma bands during the feedback timeframe (.9-3s after a response was given) on trials that resulted in a gain. All results in this table are insignificant.

Appendix H

Insignificant two-way ANOVA results investigating the effect of gender and stress on participants' average coherence between each brain comparison region within the three bands during trials that result in a gain. Electrical activity is captured while feedback is displayed.

Region	Interaction	Gender	Stress
Right vmPFC/OFC & posterior	0798(*.500*)	2.334(*.082*)	0.934(*.430*)

A table of F-values (p-value) for multivariate analyses investigating the interaction between gender and stress, the main effect of gender, and the main effect of stress. Dependent variables include average coherence within the theta, beta, and gamma bands during the feedback timeframe (.9-3s after a response was given) on trials that resulted in a gain. Results in this table are insignificant.

Appendix I

Insignificant two-way ANOVA results investigating the effect of gender and stress on participants' average power within the three bands at each brain region during trials that result in a loss. Electrical activity is captured while feedback is displayed.

Region	Interaction	Gender	Stress
Right vmPFC/OFC	1.964(*.129*)	1.800(*.157*)	1.623(*.193*)
Left vmPFC/OFC	2.175(*.100*)	2.084(*.112*)	2.654(*.056)*
Right posterior	3.000(*.094*)	1.817(*.153*)	1.911(*.137)*
Left posterior	2.170(*.101*)	2.015(*.121*)	1.775(*.161)*

A table of F-values (p-value) for multivariate analyses investigating the interaction between gender and stress, the main effect of gender, and the main effect of stress. Dependent variables include average amplitude within the theta, beta, and gamma bands during the feedback timeframe (.9-3s after a response was given) on trials that resulted in a loss. All results in this table are insignificant.