Aversive Learning and Discrimination:

The Impact of Monetary Loss on Visual Perception

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Abstract

Aversive learning has been demonstrated to alter perceptual discrimination abilities across sensory domains. Recent research has discovered that visual aversive learning with negative images leads to generalization of visual perceptual stimuli. The present study aims to determine whether visual aversive learning increases or decreases discrimination abilities after learning an association with monetary loss. The study also explores the relationship between perceptual processes and the clinical disorders of anxiety and obesity, building on past research that links overgeneralization of fearful stimuli with anxiety disorders and impaired associative learning with obesity. We test visual discrimination performance before and after an aversive learning task. Results demonstrate no significant change in visual discrimination following the learning task. However, the findings reveal a trend towards impaired aversive learning with money in overweight and obese individuals and a trend towards decreased discrimination of visual stimuli after aversive learning in individuals with anxiety. This study provides a preliminary framework for future investigation of learning and discrimination mechanisms and their clinical significance.

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I. Introduction

Organisms regularly encounter perceptual stimuli that are similar to each other but not perfectly identical. It is critical for organisms to develop and adjust their perceptual abilities in order to adapt to new environments for survival (Guttman & Kalish, 1956; Hovland, 1937; Shalev et al., 2018; Webster, 2012). When one stimulus is threatening, the difference between these stimuli is important and must be differentiated. Other situations necessitate generalizing two similar stimuli so that they are perceived as the same, such as when a group of stimuli are dangerous. However, it remains unclear which contexts or environmental variables enable increased or decreased perceptual discrimination of similar stimuli.

Associative learning has been proven to augment and diminish perceptual discrimination in both animals and humans. Prior research using a paired learning and discrimination paradigm provides evidence that discrimination abilities can change after learning associations with rewards or losses (Dymond et al., 2014; Hovland et al., 1937; Laufer & Paz, 2012; Zhang et al., 2018). Aversive learning paradigms are used to condition individuals to associate a given stimulus with a negative consequence. As a means of survival, species have evolved to learn to avoid cues that predict threatening, dangerous, or unappealing outcomes (Ginsburg & Jablonka, 2010; Lindstrom et al., 2016). A recent study investigating how aversive learning affects perceptual discrimination has found that using unpleasant pictures decreased the ability to distinguish between similar stimuli (Shalev et al., 2018). Yet, many of the choices that people face in modern-day life involve consequences of money rather than unpleasant images. The present study aims to determine the impact of aversive learning with monetary losses on individual discrimination abilities.

Given that the present study collects information on state anxiety and body mass index (BMI), this perceptual question has important implications in clinical settings for patients with anxiety disorders and obesity. First, the generalization of perceptual stimuli observed in this study might contribute to the body of literature that has linked perceptual overgeneralization to anxiety disorders. (Dunsmoor & Paz, 2015; Lenaert et al., 2014). Second, the present study will build on recent findings of impaired associative learning with food rewards in obese women. This study hopes to inform future research on aversive learning and discrimination behaviors in order to improve treatments for these patient populations.

1.1 Discrimination

Perception shapes the experience of being alive. The ability to recognize a stimulus through auditory, visual, olfactory, tactile or gustatory perception is what enables organisms to interact with their environment. For humans, environmental stimuli can elicit conscious emotions, such as desire, fear, or indifference, as well as unconscious perceptual changes (Vervliet et al., 2013). However, similar stimuli in the environment can be difficult to differentiate.

The capacity to discriminate between similar stimuli varies across individuals (Mollon, 2017; Witkin, 1950). A just noticeable difference (JND) is a measure of the smallest discriminable difference between two similar stimuli (Guttman & Kalish, 1956; Hovland, 1937). JNDs are a useful measure of individuals' intrinsic perceptual thresholds under a given set of circumstances. JNDs have been identified and measured across perceptual domains using visual, auditory, olfactory, and tactile stimuli (Davarpanah & Heath, 2014; Li et al., 2008; Shalev et al., 2018). To quantify the impact of an intervention on perception, individual JND values can be

measured before and after an intervention to observe how the intervention alters perceptual ability.

Discrimination in the visual domain is prevalent in many aspects of everyday life. For example, visual discrimination is necessary for identifying different cans on the grocery store shelf or different faces in a crowd. Within the domain of visual perception, individual differences in perception may be a result of varied visual acuity or variation in brain structure or function. Although examining between-subject visual discriminatory ability across a population or study sample can inform research on general human perception, observing within-subject changes in discriminatory ability before and after an event can inform research on the malleability of human perception.

1.2 Associative Learning

Associative learning is the process by which organisms acquire an understanding of the relationship between two or more elements. Under experimental conditions, associative learning is tested by pairing a conditioned stimulus (CS+) with an outcome at a given frequency. After a given number of pairing trials, participants learn to expect the outcome when primed with the CS+. Reward learning involves pairing stimuli with positive outcomes, while aversive learning involves pairing stimuli with negative outcomes.

In the early twentieth century, Ivan Pavlov was a pioneer in the field of conditioning that built a framework for how to study learning behaviors (1927). Reward learning has been extensively investigated across experimental domains since Ivan Pavlov's original conditioning experiments with dogs in the early twentieth century. These experiments famously demonstrated classical conditioning by pairing a bell stimulus with the reward of food and observing the dog's salivation, an unconditioned response at a given frequency. Salivation after hearing the bell

marked successful learning of the association between the bell and the food in the dog. Aversive

learning, or fear conditioning, pairs stimuli with negative outcomes at a given frequency. The

individual learns to expect the negative outcome immediately after perceiving the stimulus.

Simultaneously to his investigation of reward learning, Pavlov used classical conditioning to

successfully teach animal models to fear stimuli that have been associated with a threatening

outcome.

Since Pavlov's groundbreaking research, many researchers have examined the behaviors

of fear conditioning using a wide variety of stimuli and outcomes (Grice, 1948; Guttman &

Kalish, 1956; Hovland, 1937). Although classical conditioning has been extensively used to

study associative learning in animal models, it has also been effectively tested in humans (Reiss,

1980; Struyf et al., 2015; Zhang et al., 2018). Recent technological and methodological

innovations have sparked renewed interest in the neurobiology and clinical salience of aversive

learning and generalization, specifically the investigation of how learning impacts perceptual

discrimination.

1.3 Discrimination Learning

Discrimination learning describes associative learning that is applied to research on

perceptual discrimination in order to determine how learning changes human perception of

stimuli that one encounters in the world. There is general agreement across previous studies on

reward learning and discrimination that reward learning leads to increased perceptual

discrimination (Pascucci et al., 2015; Seitz et al., 2009; Zhang et al., 2018). However, there is no

consensus on the influence of aversive learning on discrimination. Although fear conditioning

has been repeatedly proven to influence perception, prior research has demonstrated mixed

evidence of both increased and decreased discrimination abilities following aversive learning tasks.

Like many other species, humans have evolved to learn associations between certain cues and threats in order to avoid dangerous or unfavorable outcomes (Lindstrom et al., 2016). Learning associations between stimuli and negative outcomes can impact the ability to discriminate between perceptual stimuli that are similar to the CS. Attempts to quantify the magnitude and direction of this impact have produced mixed results. Some studies that use olfactory stimuli have found that aversive learning enhances the ability to discriminate between odor cues (Li et al., 2008; Parma et al., 2015). Evidence of increased olfactory discrimination has been explained by increased plasticity of the olfactory cortex following aversive learning. Nevertheless, a larger proportion of research has also found aversive learning to deteriorate discrimination skills when using sounds and smells as aversive reinforcers (Dunsmoor & Paz, 2015; Laufer & Paz, 2012; Resnik et al., 2011). These findings of decreased discrimination align with Pavlov's historic conditioning experiments (1927). A decreased ability to distinguish between stimuli is termed generalization.

A recent study has implemented an associative learning task that pairs visual and auditory stimuli with aversive images (Shalev et al., 2018). These findings provide further evidence that aversive learning diminishes perceptual discrimination ability, thus producing greater generalization between similar visual stimuli. The study offers a neural explanation that the decrease in JND is caused by a central multimodal brain network that alters perceptual properties following exposure to a negative event. Shalev et al. propose that increased generalization is a defensive behavior which has evolved to protect the organism against the possibility of aversive outcome (2018). We model the present study after the experimental design of Shalev et al. by

testing discrimination ability with visual stimuli before and after aversive learning. However, the present study substitutes a learned aversive outcome of monetary losses in place of unpleasant images due to the prevalence of monetary consequences in everyday life.

II. The Present Study

2.1 Significance

The present study aims to determine the impact of aversive learning with monetary losses on individual visual discrimination abilities. Discrimination is dictated by perceptual capacities in the brain. Of all perceptual abilities, vision is the dominant sensory domain in humans. Much of the environment that is perceived in everyday life is processed by the visual cortex. Individuals learn associations between the things they see with various outcomes based on contextual information. Therefore, the effect of aversive learning on discrimination of visual stimuli plays an important role in daily life. Similarly, monetary losses are used in the present study as aversive learning outcomes because of their everyday salience and non-invasive nature. Previous studies have examined aspects of this perceptual learning model, but never combined visual aversive learning with money loss. The present study offers a novel, preliminary investigation on the impact of aversive learning on visual perception. We aim to provide evidence that aversive learning leads to generalization of similar stimuli. This research has potential implications of revealing psychological and neural mechanisms that drive perception and learning behavior. Understanding individual differences could have clinical applications in tailoring treatments for individuals with anxiety disorders or obesity.

2.2 Hypotheses

2.2.1 Hypothesis 1. We hypothesize that within-subject discrimination thresholds (JNDs) will increase following an aversive learning task that pairs visual CS+ with the aversive outcome of monetary loss, but that discrimination thresholds for CS- will not change significantly. This expectation is based off recent findings that visual aversive learning decreases perceptual capacity to discriminate between stimuli that have been paired with aversive images (Shalev et al., 2018).

2.2.2 Hypothesis 2. The study aims to conduct an exploratory analysis that finds relevant dimensions of learning and discrimination performance using measures such as gender, BMI, and state-trait anxiety measures. Study findings on individual differences have the potential to be further examined in follow-up studies on impaired learning and discrimination in anxiety disorders or obesity.
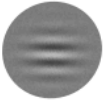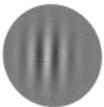
III. Methods

3.1 Participants

Participants were recruited from a pool of past participants in the Decision Neuroscience Lab and flyers posted across Yale University and Downtown New Haven. Participants included healthy individuals (*N*= 24, 13 female) with ages ranging from 19-36 (*M*= 23.92, *SD*= 4.96.) Prior to their participation, participants were informed that they would receive $10 compensation with the opportunity for further monetary earnings based on the task.

3.2 Experimental Design

The experimental code was developed on PsychoPy using the programming language of Python. The script was built off a discrimination staircase framework previously designed by Michael Grubb. Participants were assigned into one of four experimental groups. A 2 x 2 design was used to counterbalance 2 variables (Figure 1). The first variable indicated whether the CS+

has horizontally-oriented or vertically-oriented striped circles and the second variable indicated

the order of CS+ and CS- in the discrimination task. This structure aimed to eliminate anticipated

effects of the stimulus itself on behavior, including stimulus order and participant ease of

discriminating circles within the horizontal vs. vertical domains. Gabor stimuli were used in a

staircase model to measure perceptual discrimination thresholds. Gabors are frequently used as a

measure of individual perceptual capability in the field of research on visual perception.

		Horizontal → Vertical Discrimination	Vertical → Horizontal Discrimination
	Horizontal CS+	Group 1	Group 2
	Vertical CS+	Group 3	Group 4

Figure 1. Experimental Group Assignment. CS+ assignment and stimulus order were counterbalanced across subjects.

Gabor orientation was chosen as the method of determining a measurable discrimination

threshold in agreement with the design of the Shalev et al. visual aversive learning task (2018).

Although Shalev et al. measured visual stimuli discrimination using both orientation and color

contrast, color contrast was not used in the present study due to the lack of specificity in color

contrast differences on the experimental computer screen. Altering the orientation of stripes

provided a useful measure of discrimination that could be incrementally adjusted in order to

determine individual discrimination capabilities. Gabor stripes can be oriented at any given

rotation angle from a baseline orientation. The horizontal baseline orientation was exactly

horizontal across the circle (0 degrees), parallel to the horizon. The vertical baseline orientation

was exactly vertical across the circle (90 degrees), perpendicular to the horizon. In the present

study, Gabor orientations were rotated either clockwise or counterclockwise from a baseline orientation of vertical or horizontal. Orientations from the baseline ranged from 0 to 32 degrees in either the clockwise or counterclockwise direction.

Within each of the horizontal and vertical discrimination tasks, individual discrimination thresholds were determined using 2 opposing staircases. A two-down one-up staircase was modeled after the experimental design used by Shalev et al. (2018). Staircase A operated top-down, starting at the furthest orientation from the baseline (32 degrees) and incrementally decreasing to the individual's discrimination threshold. Staircase B operated bottom-up, starting at the nearest orientation from the baseline (0.5 degrees) and increasing to the individual's discrimination threshold. Two consecutive correct answers on each staircase yielded a decrease to the next lowest orientation, unless the orientation had already reached the lowest rung on the staircase (0.5 degrees). One incorrect answer on each staircase yielded an increase to the next highest orientation. The staircases converged at the orientation where the participant had difficulty determining the correct orientation direction as either clockwise or counterclockwise. The staircases provided a two-measure approach to the discrimination threshold in order to increase the reliability of the measure.

3.3 Procedure

The present study consisted of 3 consecutive tasks and 2 follow-up questionnaires. The study measured individual discrimination thresholds for the CS+ and CS- before and after learning an association between the CS+ and an aversive outcome (Figure 2). Experimental instructions were given to participants prior to each task, as well as prior to each block within the discrimination tasks. Instruction tutorials were displayed prior to each task as pre-recorded

videos with example trials and voice narration in order to establish consistency across participants.
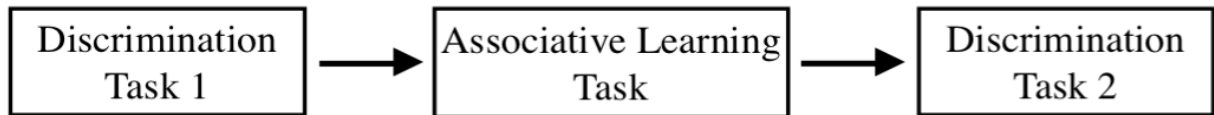
Figure 2. Discrimination Learning Experimental Paradigm.

    3.3.1 Discrimination Task 1. The first discrimination task presented 2 blocks of 80 trials each for the CS+ and CS-, or 4 blocks total. During each trial, the Gabor appeared in a foveal presentation at the center of the screen for a duration of 100 milliseconds. Participants used the arrow keys to determine whether the presented Gabor had stripes oriented more clockwise or counterclockwise from the baseline orientation. Figure 3 illustrates example Gabors that are rotated clockwise and counterclockwise in the vertical and horizontal domains. Right and left arrow keys were used for the CS- trials. The right key indicated counterclockwise and the left key indicated clockwise from the 0-degree baseline orientation. Up and down arrow keys were used for the CS+ trials. The up key indicated counterclockwise and the down key indicated clockwise from the 90-degree baseline orientation. The CS+ and CS- circle assignments (horizontal or vertical) were counterbalanced across participants. After each Gabor was presented, the subject was given an unlimited amount of time to choose an arrow key. Once an arrow key was chosen, the subject received feedback from the fixation target at the center of the screen. The target temporarily changed color from white to green for a correct response or from white to pink for an incorrect response. The feedback disappeared before the Gabor in the next trial appeared on the screen.
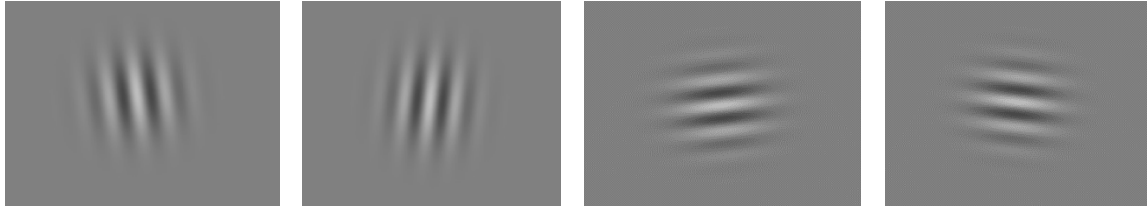
Figure 3. Vertical Counterclockwise, Vertical Clockwise, Horizontal Counterclockwise, Horizontal Clockwise Gabor Stimuli Examples. Vertically Striped and Horizontally Striped circles were counterbalanced as CS+ and CS-.

3.3.2 Learning Task. After the two discrimination blocks were completed for each stimulus, the learning task begun. The task consisted of 24 trials for each CS+ and CS-, or 48 trials total. In this task, Gabor stripes were only oriented at the baseline vertical (90 degrees) or horizontal directions (0 degrees). Each participant was given $50 during the instructions for the learning task, which they were told was theirs to keep for the duration of the task. During each trial, the participant was shown a Gabor for 3 seconds and asked to indicate how likely they think it is that an "event" will follow the Gabor (Figure 4). Events were a loss in the amount of money that the participant is given, demonstrated in a "-$3.00" sign that appeared after the Gabor disappears. Participants chose their rating from a continuous scale of 1-9, where 1 indicated that an event is very unlikely and 9 indicated that an event is very likely. Participants were informed that they may choose any number along the continuous scale. Events occurred during 50% (12) of the 24 CS+ trials and 0 of the 24 CS- trials (Figure 5). The 50% event frequency was determined based on prior pilot studies as a rate that enabled gradual subject learning throughout the task. Therefore, each participant lost a total of $36 during the 48 trials out of the $50 endowment. Each participant was left with $14 in earnings from the learning task.

Figure 4. Example of Learning Task Trial. Participants rate (1-9) the likelihood that an event will follow the circle.
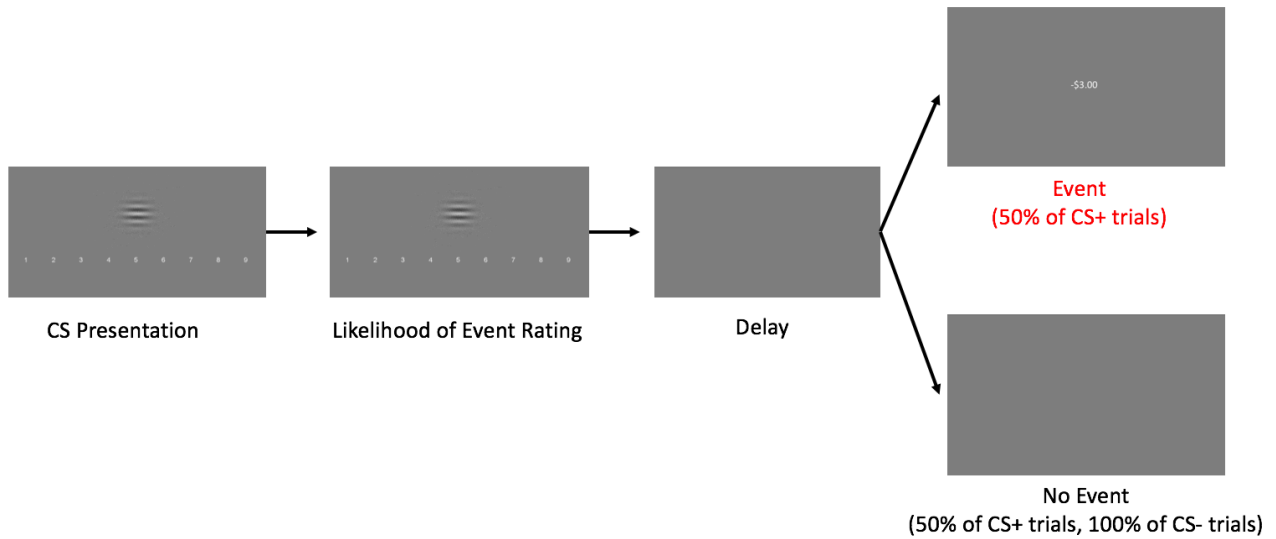
Figure 5. Within-Trial Learning Task Paradigm.

Learning data was collected from each participant's ratings for the likelihood that an event would follow the circle across the 48 trials of CS+ and CS-. We looked at whether and how these ratings changed over the course of the task to determine whether each participant

successfully learned to associate the CS+ with monetary loss. Temporal changes were

determined by dividing the trials from the first half of the learning task (early acquisition) and

the trials from the second half of the learning task (late acquisition).

To measure the efficacy of the learning task, three learning indices were derived from the

participant event likelihood ratings and acquisition phases. The difference in likelihood ratings

between CS+ and CS- was calculated from the mean likelihood ratings. The first index (ACQ)

measured how much the CS+ and CS- ratings differed during the late acquisition phase. Two

learning indices were used to measure how much learning occurred for each subject within the

CS+ and CS-. The second index (ΔCS+) quantifies how much CS+ likelihood ratings changed

throughout the task by taking the difference between the mean values of CS+ in early and late

acquisition. Similarly, the third index (ΔCS-) quantifies how much CS- likelihood ratings

change by taking the difference between the mean values of CS- during early and late

acquisition.

Index 1. $ACQ = CS+_{\text{late acquisition}} - CS-_{\text{late acquisition}}$

Index 2. $\Delta CS+ = CS+_{\text{late acquisition}} - CS+_{\text{early acquisition}}$

Index 3. $\Delta CS- = CS-_{\text{late acquisition}} - CS-_{\text{early acquisition}}$

3.3.3 Discrimination Task 2. The third task was identical in structure to the first

discrimination task. Participants were shown a refresher instruction video prior to starting each

of the CS+ and CS- blocks. Distinct discrimination thresholds were measured for the CS+ and

CS- in the first and third experimental tasks. The change in orientation discrimination thresholds

before and after aversive learning were recorded for each stimulus.

Performance in the two discrimination tasks was measured by calculating four Mean Tilt

values for each participant, measured in degrees. In addition to using a bidirectional staircase,

this method aimed to determine the orientation at which the participant had difficulty distinguishing the direction of the stimulus. Four Mean Tilt values were recorded for each participant, one for each CS+ and CS- domain before and after the learning task (preCS+, preCS-, postCS+, postCS-). Mean Tilt values were calculated by deriving the mean orientation of Gabors from the last 10 trials of Staircase A and the last 10 trials of Staircase B and they are measured in degrees. This measure of discrimination was used to examine whether and how visual perception changed after the learning task.

3.3.4 State Trait Anxiety Inventory Y-1 Form. Immediately following Task 3, participants were administered the State Trait Anxiety Inventory Y-1 form as a self-reported measure of anxiety at the time of the task (Spielberger & Donald, 1971) using the online survey platform Qualtrics. The survey consists of 20 statements about how one feels at the present moment. Participants chose between answers of "not at all," "somewhat," "moderately so," and "very much so" in response to each statement. S-anxiety scores can range from 20-80. A cutoff point of 39-40 was used to distinguish normal symptoms from clinically significant symptoms (Julian, 2011).

3.3.5 Post-Study Survey. Participants were administered a 4-question survey aimed to determine self-reported task comprehension and difficulty. The final question on the survey asked participants to report fatigue and hunger levels before and after the experiment.

3.3.6 Additional Measures. Participant age, race, ethnicity, gender, height, weight, and highest education level were also collected.

3.3.7 Payment. During study recruitment, participants were informed that they would receive $10 compensation for completing the experiment with the opportunity to receive additional earnings during the experiment. The value of task earnings was left purposefully

ambiguous so that monetary losses throughout the aversive learning task felt tangible and important. Over the course of Task 2, participants lost $36 of the $50 endowment they were given. They were allowed to keep the remaining $14 from Task 2 in addition to the $10 compensation, leaving each participant with a total sum of $24 from the experiment. Participants were only informed of their net earnings after the entire experiment was completed.

IV. Results

4.1 Learning Results

Learning performance was measured by examining changes in participant likelihood ratings over the course of the 48 task trials. The early acquisition phase consisted of trials 1-24 while the late acquisition phase consisted of trials 25-48. Figure 6 demonstrates one participant's course of learning throughout the task and exemplifies a noticeable divergence in CS+ and CS-likelihood ratings during the late acquisition phase. Figure 7 illustrates the average likelihood ratings across all subjects for each of the 24 CS+ and 24 CS- trials. Mean CS+ and CS- ratings diverge quickly in the early acquisition phase.
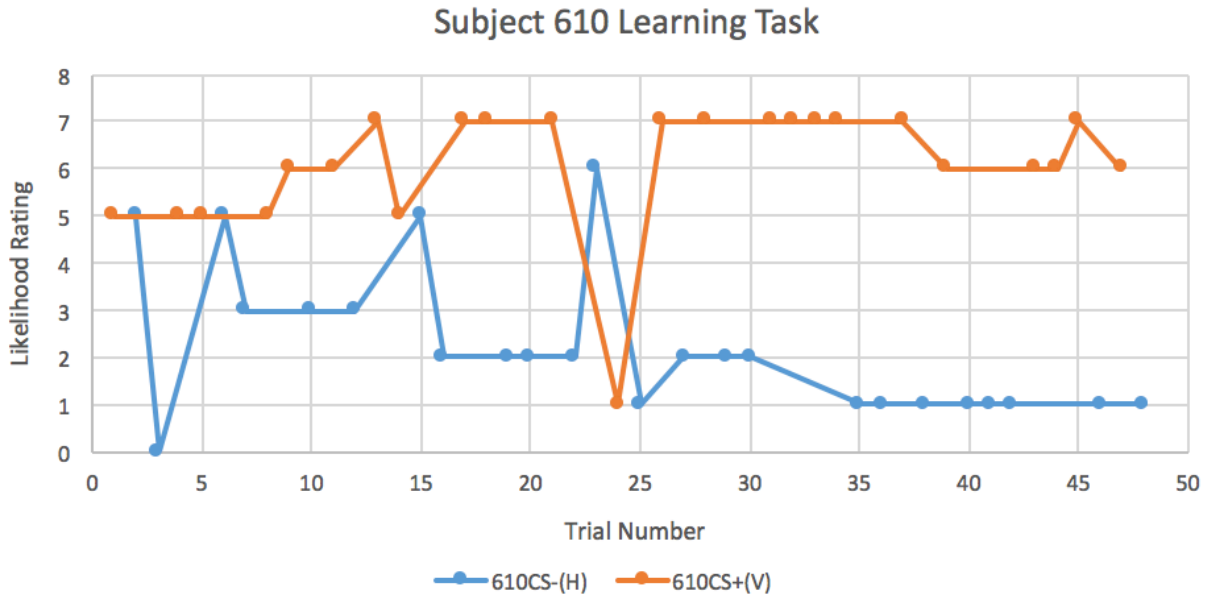
Figure 6. Example of successful learning during task in Subject 610. CS+ and CS- likelihood ratings diverge during the late acquisition phase.
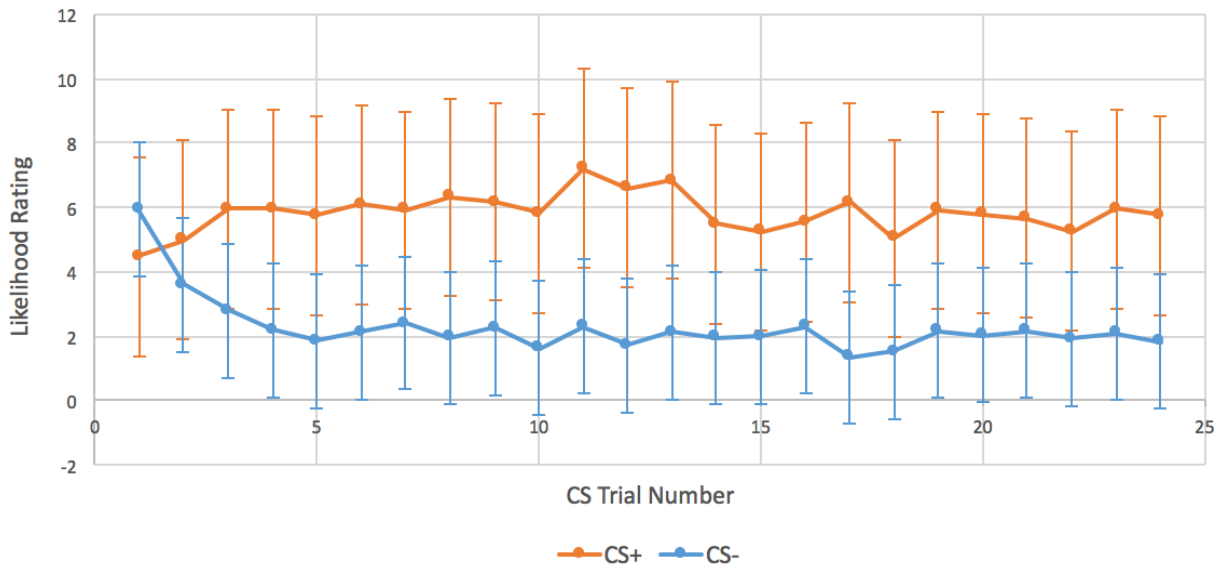
Figure 7. Mean CS+ and CS- likelihood ratings across all subjects. Divergence between mean CS+ and CS- occurs prior to trial 5 in the early acquisition stage, indicating that the majority of participants learned quickly during the task. Error bars represent the standard deviation of participant likelihood ratings.

Subject learning during the learning task was quantified using three indices, ACQ, ΔCS+, and ΔCS- (Figure 8). Although there was a wide range of ACQ scores (10.58), most participants demonstrated learning through a divergence in their likelihood ratings for CS+ and CS- (*M*=3.82, *SD*=2.41). However, ΔCS+ (*M*=0.31, *SD*=1.61) and ΔCS- (*M*=-0.23, *SD*=0.92) values aggregated close to 0, indicating no substantial change in the mean likelihood ratings between the early and late acquisition stages for a majority of participants (Figure 8).
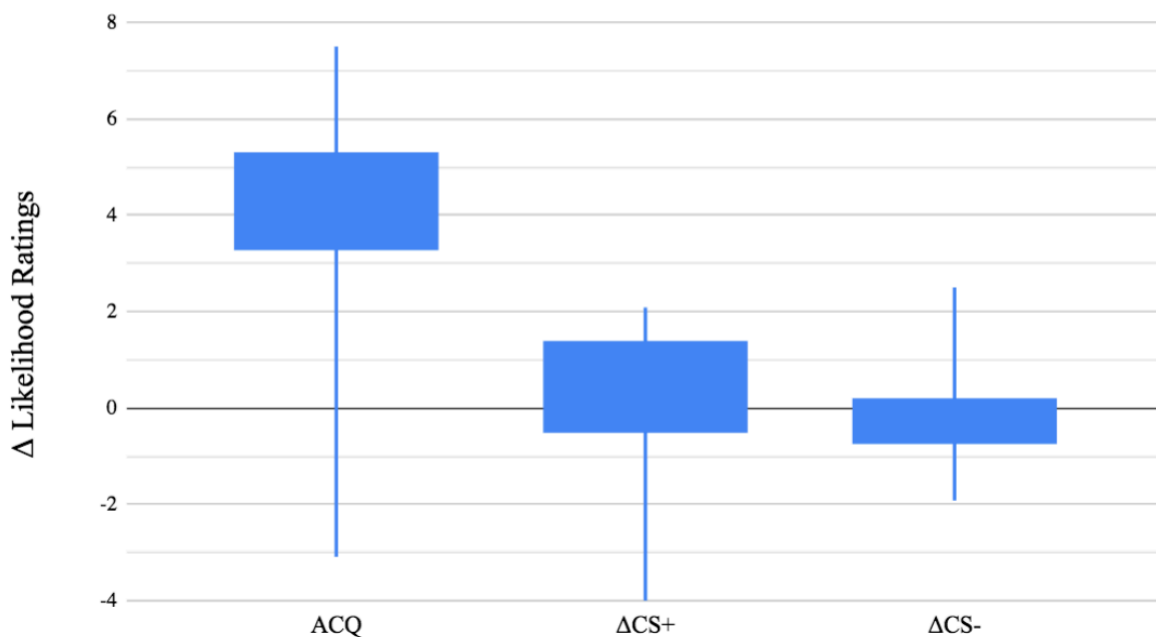
Figure 8. ACQ, ΔCS+, and ΔCS- indices. Box plots demonstrate minimum, quartile, and maximum values of each index. Positive mean and quartile ACQ values demonstrated a significant divergence in likelihood ratings for CS+ and CS- across a majority of participants.

4.2 Individual Differences in Learning

Group differences and correlations were examined to determine the relationship between learning and gender, anxiety, and obesity. There were no significant differences in ACQ between males (*M*=4.12, *SD*=1.74) and females (*M*=3.61, *SD*=2.95), t(22)=2.07, p=0.65. S-anxiety scores varied across participants (*M*=41.63, *SD*=10.48). Between participants with normal S-anxiety scores (*M*=32.73, *SD*=4.56) and clinically significant STAI-Y1 anxiety scores (*M*=49.15,

SD=7.7), there was no significant difference in ACQ, t(22)=2.07, p=0.45. We also found no

significant correlation between STAI-Y1 anxiety scores and ACQ, *r*(22)=0.11, p=0.59 (Figure

9).
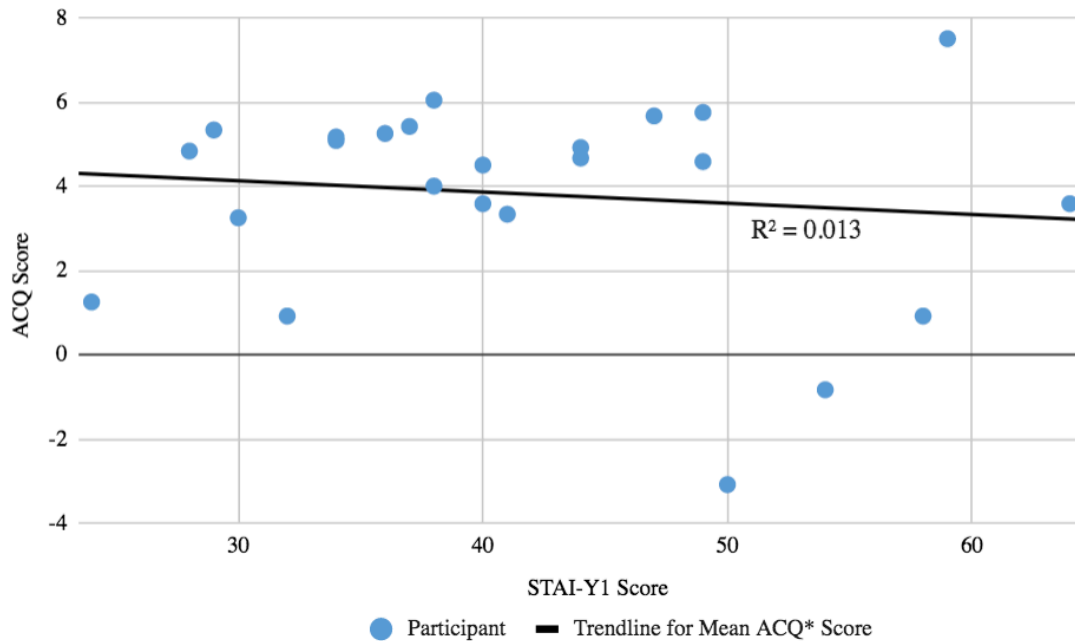
Figure 9. ACQ score is negatively but not significantly correlated with ACQ.

The results from the learning task demonstrated a trending significant difference between

normal and overweight or obese individuals. Although the majority of participants in the

experimental sample had BMI values within the normal range (BMI 18.5-24.9), there were two

participants with BMI values within the overweight range (BMI 25.0-29.9) and one within the

obese range (BMI≥30.0). Between normal weight participants (*M*=22.23, *SD*=1.89) and

overweight or obese participants (*M*=27.49, *SD*=2.60), we identified a trend towards a significant

differences in ACQ scores, t(2)=4.30, p=0.08. More data are needed to verify the strength of the

relationship between BMI and aversive learning with monetary outcomes, specifically from a

larger sample of overweight or obese individuals. However, we found no significant correlation between BMI and ACQ, $r(21)=0.07$, p=0.72 (Figure 10).
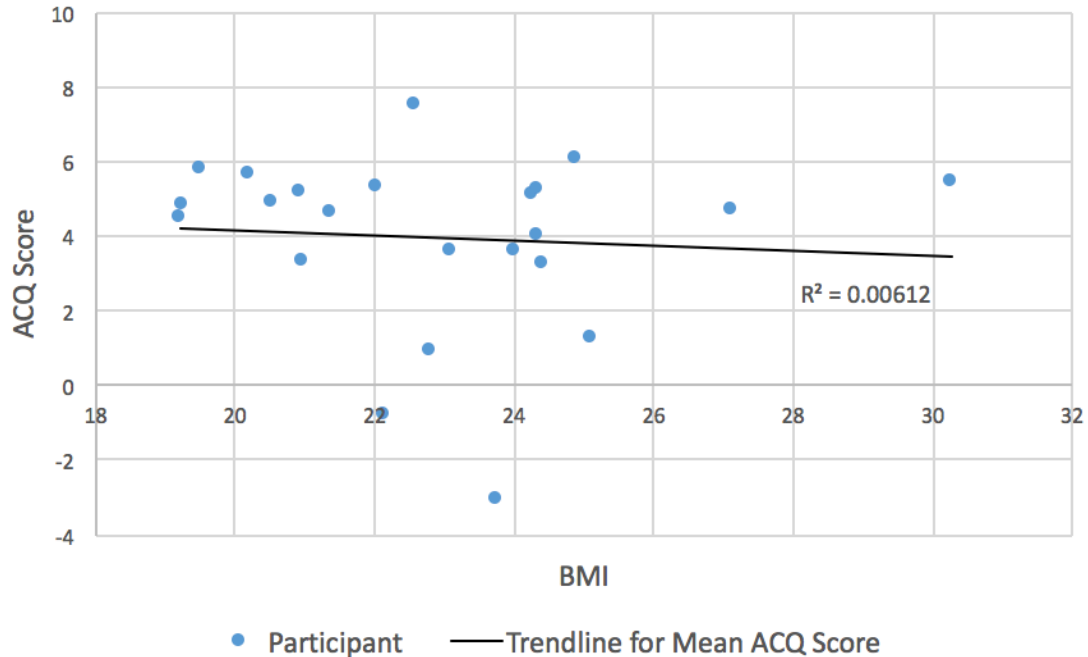
Figure 10. ACQ Score is negatively but not significantly correlated with BMI.

4.3 Discrimination Results

Discrimination performance was measured in Mean Tilt values for CS+ and CS- before and after learning for each subject (Figure 11). Subject 620 was excluded from all discrimination analysis because the discrimination accuracy values drifted around chance (0.5), or the accuracy of a blind guess. We found no significant differences in the Mean Tilt Values between or within stimuli (Figure 12). However, we found trending significance that CS+ discrimination improved after learning. Against our hypothesis that CS+ would yield higher Mean Tilt values than CS- after learning, there was no significant difference between the postCS+ and postCS-, t(44)=2.01, p=0.71. We also found the predicted result that there would be no significant difference between the preCS+ and preCS-, t(45)=2.01, p=0.31. As expected, we found no significant difference in

Mean Tilt between preCS- (M=1.13, SD=0.51) and postCS- (M=1.06, SD=0.51), t(43)=2.01,

p=0.67. However, against our hypothesis that postCS+ would have a greater tilt than preCS+, the

results trended towards a significant difference between the preCS+ (M=1.37, SD=1.00) and

postCS+ (M=1.02, SD=0.36), t(44)=2.02, p=0.11. More data must be collected to determine the

strength of the relationship between preCS+ and postCS+ Mean Tilts.
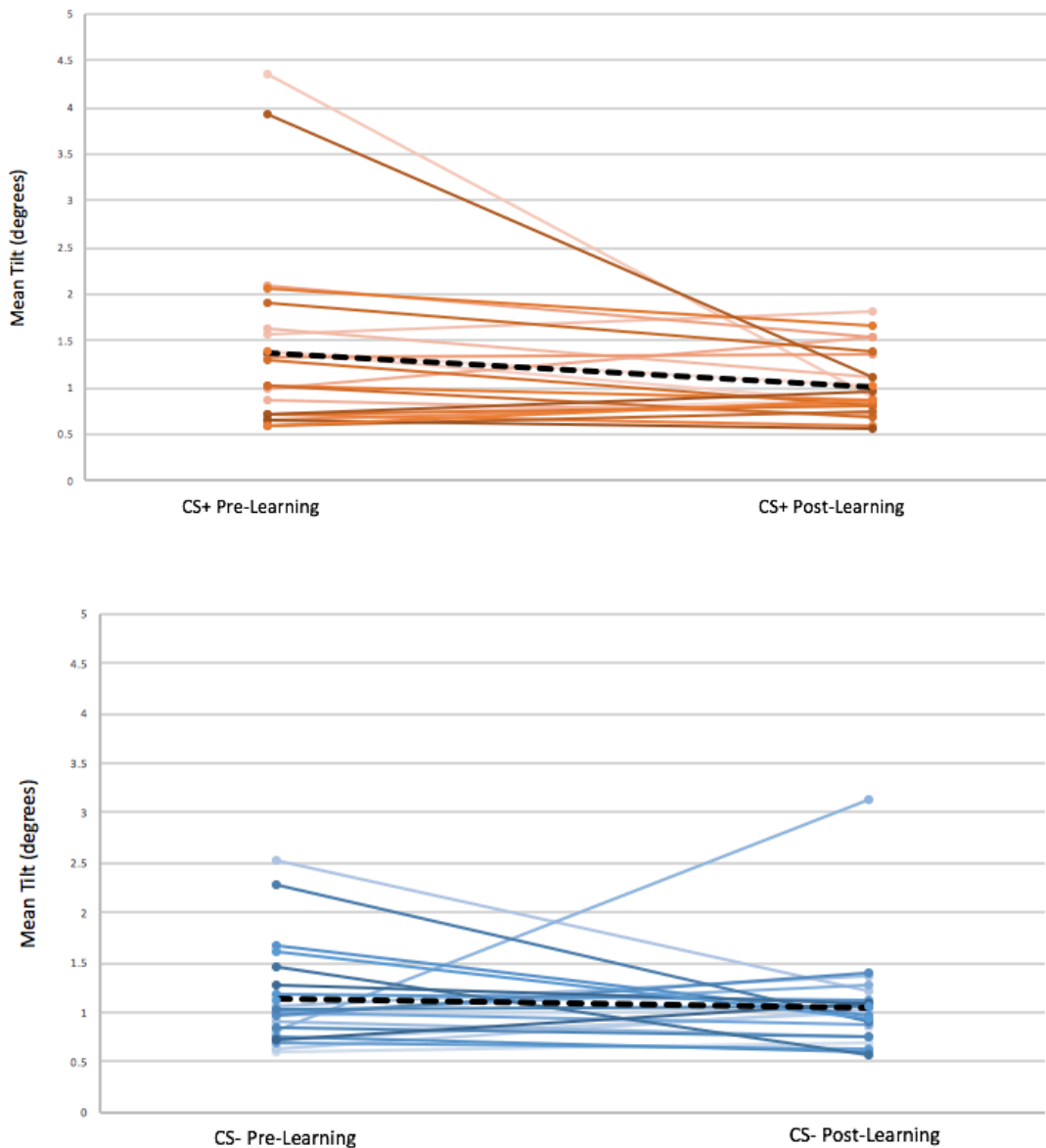
Figure 11. Each colored line represents the change in Mean Tilt for one subject in the CS+ or CS- tasks. The dashed black line represents the mean change in tilt values across participants.
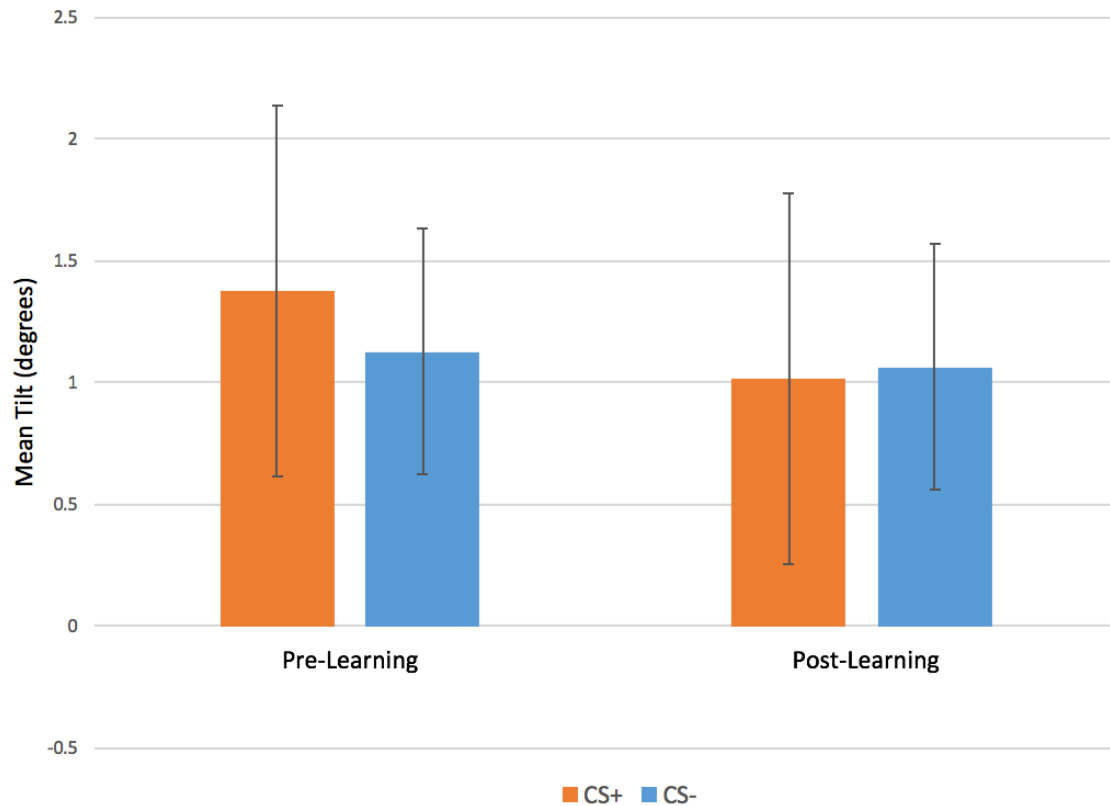
Figure 12. There was no significant difference between the Mean Tilt values within or between CS+ and CS- across the pre- and post-learning phases across participants.

We looked at the relationship between learning and discrimination performance by correlating subject ACQ Scores with the changes in Mean Tilt of CS+ and CS-, as well as with the difference between CS+ and CS- changes in Mean Tilt [(postCS+ – preCS+) – (postCS- – preCS-)]. The latter measure was aimed at controlling any differential changes in threshold that are due to improved discrimination task performance or fatigue. We expected to see a strong correlation between ACQ (successful learning) and a negative change in CS+ but no correlation with CS-. Contrary to our hypothesis, there was no significant correlation between ACQ and CS+, $r(22)=0.13$, $p=0.55$. However, as expected, there was also no significant correlation

between ACQ and CS-, r(21)=0.07, p=0.74. Lastly, we found no significant correlation between ACQ and the difference between CS+ and CS- changes in Mean Tilt, r(22)=0.16, p=0.45.

4.4 Individual Differences in Discrimination

Discrimination performances yielded no notable differences by gender, BMI, or state anxiety. There was no significant difference in the change in discrimination performance for CS+ (postCS+ - preCS+) between males and females, t(21)=2.08, p=0.92. There was also no gender difference in for the change in discrimination performance for CS- (postCS- - preCS-), t(21)=2.09, p=0.78. Neither state anxiety nor BMI seemed to impact changes in discrimination performance across the pre-and post-learning tasks. There was a trend towards a significant correlation between STAI-Y1 and change in Mean Tilt of CS+, r(22)=0.27, p=0.22. More data is needed to verify the impact of clinical symptoms on the change in CS+ Mean Tilt. However, there was no significant correlation between STAI-Y1 and change in Mean Tilt of CS-, r(22)=0.21, p=0.34. There was no significant correlation between BMI and change in discrimination of CS+, r(22)=0.08, p=0.71. There was also no evidence of a significant correlation between BMI and change in discrimination of CS-, r(22)=0.04, p=0.86.

V. Discussion

5.1 General Discussion

The hypothesized experimental outcome was that aversive learning would lead to decreased discriminatory ability. The results of the present study do not provide significant evidence supporting the hypothesized impact of learning on discrimination, but they do provide interesting insight into the development of future research on perceptual learning and in the clinical domains of anxiety disorders and obesity.

Hypothesis 1 anticipated that within-subject discrimination thresholds would increase in the CS+ after learning to associate the CS+ with an aversive monetary outcome, with no increase in CS- discrimination threshold. The hypothesized effect was not apparent in the average Mean Tilt values across subjects, which decreased across both CS+ and CS-. On the contrary, the results indicated trending significance that CS+ discrimination improved (JND decreased) after learning to associate the CS+ with money loss. This unexpected outcome suggests that subjects are more attentive to and able to perceive changes in a stimulus after aversive learning. Subject discrimination may have improved as a result of heightened sensitivity of fear of the stimulus. More data from future iterations of the study are needed to confirm this result.

The most salient explanation for why the results lacked significance is that subject performance on the discrimination tasks exceeded our expectations. Prior studies that have used Gabor orientation to measure visual perception have presented Gabors at a peripheral location on the screen, rather than a foveal location (Grubb et al., 2013; Grubb et al., 2015). The foveal presentation in the present study made the Gabor more accessible in the visual field because subjects did not have to search for the Gabor's location in addition to determining its direction. Therefore, many participants' discrimination thresholds neared 0.5 degrees, which was the lowest possible orientation on the discrimination staircases. Because of this, participant discrimination thresholds may not have been an accurate measure of JND. Many participants may have had thresholds below 0.5 degrees if the staircases extended to lower orientation values. Without accurate JND measures, it is impossible to compare participant perceptual abilities before and after learning. Inaccurate measures of subject perceptual thresholds are a likely explanation for the lack of support for Hypothesis 1. However, limitations to the present study that are addressed later on provide many other explanations for the results.

Hypothesis 2 facilitated exploratory freedom for investigating relationships between demographic measures collected in the study and performance on the learning and discrimination tasks. These relationships are best considered through examining the clinical applications of the present study's results.

5.2 Clinical Applications

The exploratory analyses conducted in this study provide novel insights about applications of learning and discrimination to future clinical research on anxiety disorders and obesity. In agreement with past research, the present study identifies trends of significance between anxiety symptoms and impaired discrimination, as well as between obesity and impaired associative learning.

5.2.1 Anxiety Disorders. Discrimination learning performance has been linked to the presence and development of anxiety symptoms and disorders. Overgeneralization of perceptual stimuli has been pathogenically linked to anxiety disorders in both non-discriminative and discriminative fear conditioning tasks (Dunsmoor et al., 2011; Dunsmoor & Paz, 2015; Dymond et al., 2014; Lissek et al., 2012; Struyf et al., 2015). Overgeneralization results from impaired discrimination learning between threatening and safe signals, contributing to the development of anxiety symptoms (Lissek et al., 2012). In dangerous contexts, generalization can result from choice behavior, perceptual changes, or an interaction of these two variables (Laufer & Paz, 2016). Preliminary research on auditory aversive learning has found that overgeneralization derives from perceptual changes (Schechtman et al., 2010). The effect of these perceptual changes have been observed as modulated representations of the stimulus in the amygdala and prefrontal cortex (Laufer & Paz, 2016). Additionally, aversive discrimination learning and generalization have been shown to predict anxiety symptoms in a clinical population at a six-

month follow-up (Lenaert et al., 2014). This result signifies the importance of individual differences in learning and discrimination as predictors of anxiety disorder development.

Discrimination behaviors observed in this study may have clinical implications in the treatment of individuals with anxiety symptoms or disorders. For example, this discrimination learning research might shape the development of exposure therapy for anxiety disorders that is tailored to treat the degree of an individual's impaired discriminatory ability. The present study examines how aversive learning impacts generalization of visual stimuli. The results provide preliminary evidence that there is a relationship between state anxiety measures and changes in perceptual discrimination after aversive learning. However, this trending significant correlation necessitates more data collection in order to determine the true nature of this relationship. Since the study fails to accurately measure individual JND, it is likely that future iterations of this study will reveal more reliable correlational evidence between perceptual changes and anxiety. Additionally, the results provide no evidence that clinical symptoms of anxiety alter an individual's aversive learning ability, as demonstrated in the past literature.

Although the present study does not utilize brain imaging methodology to identify relevant regions implicated in discrimination learning, it opens the door for further research on whether the overgeneralization behaviors seen in prior studies can translate into the domains of visual perception and monetary loss. The results of the present study may spark future investigation of how overgeneralization is influenced by learning associations with negative outcomes for individuals with clinical symptoms of anxiety or with anxiety disorders.

5.2.2 Obesity. The present study's investigation of aversive learning has potential applications in the field of obesity and decision-making. Reward circuitry dysfunction, specifically impaired dopaminergic pathway regulation, is thought to play a significant role in

obesity and binge eating (Volkow et al., 2011). Individual differences in associative learning and generalization with food (but not monetary) outcomes have been discovered in obese women (Zhang et al., 2014). Zhang et al. identified impaired learning and discrimination in obese women after they learned associations between a cue and a food reward. They observed unimpaired learning when monetary rewards were used. Zhang et al. examined associative learning using rewards but not aversive outcomes.

The present study provides a novel preliminary investigation of aversive learning in the domains of visual stimuli and monetary outcomes. The results of the present study provide preliminary evidence that BMI is correlated with impaired aversive learning using monetary losses. Although Zhang et al. used a reward learning paradigm that revealed no correlation between monetary rewards and BMI, they never tested an aversive learning paradigm. The present study suggests that impaired learning in obese individuals might not be restricted to the domain of food rewards, but they also permeate the domain of monetary loss as well. This result has never been identified in the past literature, and could have important implications in understanding the behavior of individuals with obesity. However, the small sample of three overweight or obese participants requires much more data collection within this population to confirm this relationship.

Future research comparing reward and aversive learning paradigms between obese and healthy controls might provide further insight into the relationship between learning behaviors and obesity. Modifications of the present study to compare learning with money and food outcomes would provide further insight into the relationship between obesity and perception. A later iteration of these methods might include a within-subject comparison of associative learning

in food rewards, monetary rewards, and monetary losses would contribute to the larger clinical investigation of decision-making, gender, and obesity.

5.3 Limitations

5.3.1 Generalizability. It is important to recognize the small sample size of the present study. Additionally, 18 of the 24 participants were Yale University students, indicating a higher education level and suggesting a higher IQ than the average member of the population. These sample-specific limitations may restrict our ability to generalize the results to the population at large. Furthermore, there is uncertainty about the generalizability of any laboratory research on visual perceptual learning to real world situations (Lu et al., 2011).

5.3.2 Explicit Learning Measures. To measure learning in the present study, we use the explicit measure of asking participants to rate the likelihood that an event will follow the circle in each trial of the task. Successful associative learning is measured by a significant divergence in ratings for the CS+ and CS-. The present study does not use any implicit measures of learning such as pupil dilation or skin conductance responses. While implicit learning measures could offer new insight on participant learning, implicit learning measures can be small in effect size and noisy when applied to Pavlovian conditioning tasks (Pietrock et al., 2019).

5.3.3 Discrimination Task Effects. One limitation of analyzing discrimination results is that it can be ambiguous to distinguish task effects from true experimental outcomes. One task effect might be the onset of fatigue throughout the experiment, which would negatively impact performance in Task 3. Another effect might be task improvement such that an individual's discrimination ability increases in Task 3 due to the participant having more practice than when they started Task 1, improving Task 3 discrimination performance. To eliminate these differential changes, we tested both CS+ and CS- performance after the learning task. Therefore,

threshold changes due to task effects would likely be observed consistently across CS+ and CS-, while changes due to aversive learning would only be observed for CS+.

5.3.4 Self-Reported Measures. Self-reported measures of state anxiety, height, and weight limit the accuracy of exploratory analyses that correlate task performance with individual BMI or state anxiety. However, the exploratory nature of the present study does not necessitate objective measures of BMI and anxiety. In future studies, self-reported inaccuracies might be resolved by measuring participant height and weight on site after completing the experiment and conducting an implicit measure of anxiety, such as the Implicit Association Test – Anxiety (Weck et al., 2010).

5.4 Future Directions

There are many possible future directions for this study in basic scientific and clinical domains. Primarily, the present study ought to be modified so that the discrimination tasks accurately measure participant JND in order to sufficiently determine whether aversive learning with money loss can impact perception. This could be accomplished by lowering the contrast of the stripes on the Gabor, using a shorter Gabor presentation time, or lowering the staircase orientation range below 0.5 degrees.

Further examination of the trending significant relationship between symptoms of anxiety and discrimination performance after aversive learning would provide stronger evidence for the present study's findings. A larger follow-up study should include equal representation from individuals with clinically significant anxiety symptoms and those without. It would be useful to compare the causes of visual discrimination changes by expanding the design to include both reward and aversive learning tasks.

Similarly, the trending significant correlation that we found between BMI and impaired aversive learning with monetary losses should be further investigated. A larger follow-up study could recruit an equal number of individuals that classify as normal weight and overweight or obese to ensure adequate representation for accurate population comparison. Additionally, associative learning ability could be observed for reward and aversive learning using both monetary and food rewards. This design would expand the work of Zhang et al. to determine whether overweight or obese individuals show impaired associative learning when aversive outcomes are involved.

In the domain of data analysis, the present study would be improved by adding a second method of determining individual discrimination performance to compare to the first method of identifying subject Meant Tilt values. A second approach to discrimination could fit a psychometric function to each CS+ and CS- domain before and after the learning task to produce a Threshold value, which is a point on the curve where the participant would get 75% of trials correct. In combination with the first method, the psychometric approach would provide a two-part check to ensure accurate measurement of discrimination performance (JND).

The present study explores the possibility of applying a visual aversive learning with monetary loss paradigm to a variety of fields of research. Future directions for the present study may focus on any number of these research routes with the ultimate goal of developing a concrete understanding of learning and discrimination behaviors.

VI. Conclusion

In a society where anxiety disorders and obesity are two of the most increasingly prevalent health conditions, it is critical that we zoom in to identify the psychological and neural

mechanisms that drive these behaviors (Raghupathi & Raghupathi, 2018). Understanding the

functionality and malleability of human learning and discrimination abilities will inform the

future development of improved prevention and treatment for these health conditions. The

present study does not provide evidence that supports the hypothesized outcome that aversive

learning with monetary losses alters visual perceptual discrimination abilities. Our findings

reveal unanticipated weaknesses in the present study which can be addressed in future iterations

to obtain a successful and accurate measure of visual aversive learning with monetary loss.

However, the present study sheds light on the implications of learning and discrimination

behaviors in patients with anxiety disorders, obesity, or both. It is important that future research

on perceptual learning builds on the successes and failures of the present study in order to

contribute novel evidence to the field and ultimately improve clinical outcomes.

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References

Craske, M., Stein, M., Eley, T. *et al.* Anxiety disorders. *Nat Rev Dis Primers* **3,** 17024 (2017).

  https://doi.org/10.1038/nrdp.2017.24.

Davarpanah Jazi, S., & Heath, M. (2014). Weber's law in tactile grasping and manual estimation:

  Feedback-dependent evidence for functionally distinct processing streams. *Brain and*

  Cognition, *86*, 32–41. https://doi.org/10.1016/j.bandc.2014.01.014.

Dunsmoor, J. E., Prince, S. E., Murty, V. P., Kragel, P. A., & LaBar, K. S. (2011).

  Neurobehavioral mechanisms of human fear generalization. *NeuroImage*, *55*(4), 1878–

  1888. https://doi.org/10.1016/j.neuroimage.2011.01.041.

Dunsmoor, J. E., & Paz, R. (2015). Fear Generalization and Anxiety: Behavioral and Neural

  Mechanisms. *Biological Psychiatry*, *78*(5), 336–343.

  https://doi.org/10.1016/j.biopsych.2015.04.010.

Dymond, S., Dunsmoor, J. E., Vervliet, B., Roche, B., & Hermans, D. (2015). Fear

  Generalization in Humans: Systematic Review and Implications for Anxiety Disorder

  Research. *Behavior Therapy*, *46*(5), 561–582. https://doi.org/10.1016/j.beth.2014.10.001.

Ginsburg, S., & Jablonka, E. (2010). The evolution of associative learning: A factor in the

  Cambrian explosion. *Journal of Theoretical Biology*, *266*(1), 11–20.

  https://doi.org/10.1016/j.jtbi.2010.06.017.

Grice, G. R. (1948). The relation of secondary reinforcement to delayed reward in visual

  discrimination learning. Journal of Experimental Psychology, 38(1), 1–16.

  https://oce.ovid.com/article/00004782-194802000-00001/HTML.

Grubb, M. A., Behrmann, M., Egan, R., Minshew, N. J., Heeger, D. J., & Carrasco, M.

  "Exogenous Spatial Attention: Evidence for Intact Functioning in Adults With Autism

Spectrum Disorder." Journal of Vision 13, no. 14 (2013): 9, 1-13.

https://doi.org/10.1167/13.14.9.

Grubb, M. A., White, A. L., Heeger, D. J., & Carrasco, M. (2015). Interactions between

voluntary and involuntary attention modulate the quality and temporal dynamics of visual

processing. *Psychonomic bulletin & review*, *22*(2), 437–444.

https://doi.org/10.3758/s13423-014-0698-y.

Guttman, N., & Kalish, H. I. (1956). Discriminability and stimulus generalization. Journal of

Experimental Psychology, 51(1), 79–88. https://doi.org/10.1037/h0046219.

Haddad, A.D.M., Pritchett, D., Lissek, S. et al. Trait Anxiety and Fear Responses to Safety Cues:

Stimulus Generalization or Sensitization?. J Psychopathol Behav Assess 34, 323–331

(2012). https://doi.org/10.1007/s10862-012-9284-7.

Hovland, C. I. (1937). The generalization of conditioned responses. III. Extinction, spontaneous

recovery, and disinhibition of conditioned and of generalized responses. Journal of

Experimental Psychology, 21(1), 47–62. https://doi.org/10.1037/h0055714.

Julian L. J. (2011). Measures of anxiety: State-Trait Anxiety Inventory (STAI), Beck Anxiety

Inventory (BAI), and Hospital Anxiety and Depression Scale-Anxiety (HADS-A). *Arthritis

care & research*, *63 Suppl 11*(0 11), S467–S472. https://doi.org/10.1002/acr.20561

Laufer, O., & Paz, R. (2012). Monetary Loss Alters Perceptual Thresholds and Compromises

Future Decisions via Amygdala and Prefrontal Networks. *Journal of Neuroscience*, *32*(18),

6304–6311. https://doi.org/10.1523/JNEUROSCI.6281-11.2012.

Lenaert, B., Boddez, Y., Griffith, J. W., Vervliet, B., Schruers, K., & Hermans, D. (2014).

Aversive learning and generalization predict subclinical levels of anxiety: A six-month

longitudinal study. *Journal of Anxiety Disorders*, *28*(8), 747–753.

https://doi.org/10.1016/j.janxdis.2014.09.006.

Lindström, B., Selbing, I., & Olsson, A. (2016). Co-Evolution of Social Learning and

Evolutionary Preparedness in Dangerous Environments. *PLOS ONE*, *11*(8), e0160245.

https://doi.org/10.1371/journal.pone.0160245.

Lissek, S., Powers, A. S., McClure, E. B., Phelps, E. A., Woldehawariat, G., Grillon, C., & Pine,

D. S. (2005). Classical fear conditioning in the anxiety disorders: A meta-analysis.

Behaviour Research and Therapy, *43*(11), 1391–1424.

https://doi.org/10.1016/j.brat.2004.10.007.

Lu, Z. L., Hua, T., Huang, C. B., Zhou, Y., & Dosher, B. A. (2011). Visual perceptual learning.

Neurobiology of learning and memory, 95(2), 145–151.

https://doi.org/10.1016/j.nlm.2010.09.010.

Mollon, J. D., Bosten, J. M., Peterzell, D. H., & Webster, M. A. (2017). Individual differences in

visual science: What can be learned and what is good experimental practice? *Vision

Research*, *141*, 4–15. https://doi.org/10.1016/j.visres.2017.11.001.

Norbury, A., Robbins, T. W., & Seymour, B. (2018). Value generalization in human avoidance

learning. *ELife*, *7*, e34779. https://doi.org/10.7554/eLife.34779.

Parma, V., Ferraro, S., Miller, S. S., Åhs, F., & Lundström, J. N. (2015). Enhancement of Odor

Sensitivity Following Repeated Odor and Visual Fear Conditioning. *Chemical Senses*,

40(7), 497–506. https://doi.org/10.1093/chemse/bjv033.

Pascucci, D., Mastropasqua, T., & Turatto, M. (2015). Monetary Reward Modulates Task-

Irrelevant Perceptual Learning for Invisible Stimuli. *PLOS ONE*, *10*(5), e0124009.

https://doi.org/10.1371/journal.pone.0124009.

Pavlov, I. P. (1927). Conditioned reflexes: an investigation of the physiological activity of the cerebral cortex. Oxford Univ. Press.

Pietrock, C., Ebrahimi, C., Katthagen, T. M., Koch, S. P., Heinz, A., Rothkirch, M., & Schlagenhauf, F. (2019). Pupil dilation as an implicit measure of appetitive Pavlovian learning. *Psychophysiology*, *56*(12). https://doi.org/10.1111/psyp.13463.

Raghupathi, W., & Raghupathi, V. (2018). An Empirical Study of Chronic Diseases in the United States: A Visual Analytics Approach. International journal of environmental research and public health, 15(3), 431. https://doi.org/10.3390/ijerph15030431.

Reiss, S. (1980). Pavlovian conditioning and human fear: An expectancy model. *Behavior Therapy*, *11*(3), 380–396. https://doi.org/10.1016/S0005-7894(80)80054-2.

Resnik, J., Sobel, N., & Paz, R. (2011). Auditory aversive learning increases discrimination thresholds. *Nature Neuroscience*, *14*(6), 791–796. https://doi.org/10.1038/nn.2802.

Schechtman, E., Laufer, O., & Paz, R. (2010). Negative Valence Widens Generalization of Learning. *Journal of Neuroscience*, *30*(31), 10460–10464. https://doi.org/10.1523/JNEUROSCI.2377-10.2010.

Seitz, A. R., Kim, D., & Watanabe, T. (2009). Rewards Evoke Learning of Unconsciously Processed Visual Stimuli in Adult Humans. *Neuron*, *61*(5), 700–707. https://doi.org/10.1016/j.neuron.2009.01.016.

Shalev, L., Paz, R., & Avidan, G. (2018). Visual Aversive Learning Compromises Sensory Discrimination. *The Journal of Neuroscience*, *38*(11), 2766–2779. https://doi.org/10.1523/JNEUROSCI.0889-17.2017.

Spielberger, Charles Donald, 1927-2013. (1983). State-trait anxiety inventory for adults. Sampler set. Palo Alto, CA: Mind Garden.

Struyf, D., Zaman, J., Vervliet, B., & Van Diest, I. (2015). Perceptual discrimination in fear

generalization: Mechanistic and clinical implications. *Neuroscience & Biobehavioral*

Reviews, *59*, 201–207. https://doi.org/10.1016/j.neubiorev.2015.11.004.

Vervliet, B., Baeyens, F., Van den Bergh, O., & Hermans, D. (2013). Extinction, generalization,

and return of fear: A critical review of renewal research in humans. *Biological Psychology*,

92(1), 51–58. https://doi.org/10.1016/j.biopsycho.2012.01.006.

Volkow, N. D., Wang, G. J., & Baler, R. D. (2011). Reward, dopamine and the control of food

intake: implications for obesity. Trends in cognitive sciences, 15(1), 37–46.

https://doi.org/10.1016/j.tics.2010.11.001.

Webster M. A. (2012). Evolving concepts of sensory adaptation. F1000 biology reports, 4, 21.

https://doi.org/10.3410/B4-21.

Weck, F., Bleichhardt, G., Witthöft, M. et al. Explicit and Implicit Anxiety: Differences Between

Patients with Hypochondriasis, Patients with Anxiety Disorders, and Healthy Controls.

Cogn Ther Res 35, 317–325 (2011). https://doi.org/10.1007/s10608-010-9303-5.

Witkin, H. A. (1950). Individual Differences in Ease of Perception of Embedded Figures.

Journal of Personality, *19*(1), 1–15. https://doi.org/10.1111/j.1467-6494.1950.tb01084.x

Zhang, P., Hou, F., Yan, F.-F., Xi, J., Lin, B.-R., Zhao, J., … Huang, C.-B. (2018). High reward

enhances perceptual learning. *Journal of Vision*, *18*(8), 11. https://doi.org/10.1167/18.8.11.

Zhang, Z., Manson, K. F., Schiller, D., & Levy, I. (2014). Impaired Associative Learning with

Food Rewards in Obese Women. *Current Biology*, *24*(15), 1731–1736.

https://doi.org/10.1016/j.cub.2014.05.075.