Anger and Pavlovian Bias: Integrating Laboratory Task Performance and Ecological Momentary Assessment

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by

Joseph A. Wonderlich
Master of Arts
George Mason University, 2016
Bachelor of Arts
Saint John's University, 2010

Director: Sarah Fischer Nowaczyk, Associate Professor
Department of Psychology

Summer Semester 2020
George Mason University
Fairfax, VA

DEDICATION

This is dedicated to my family, especially my Mom and Dad. They have provided me with unwavering support throughout my life and have taught me that any obstacles or challenge put in front of me can be overcome if I just “use two hands”.

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First, I would like to thank Dr. Sarah Fischer Nowaczyk. I could not have asked for a better mentor and friend. She has stood by me, and this project, through countless obstacles, while never losing faith that I could overcome anything, including the black cloud. From start to finish, she has been invaluable in every stage of this project. Second, I would like to thank Dr. James Thompson for allowing me to use so much of his time. Jim has been a vital contributor to my dissertation, from teaching me what EEG stands for to walking me through computational models. Even a case of beer is not enough to say thank you. Third, I would like to thank Dr. Tara Chaplin for serving as a committee member and for providing me with important insight that was ultimately shaped this project. Next, I would like to thank Joe Dinh, Christine Reha, Helen Brandt, and Hans Christian Lauritzen for being truly the best research assistants that I could have asked for. Without these four, this project would have never left the ground. I am so grateful to have been able to work with you all. I would to thank my lab twin, Catherine Byrne, for getting me through graduate school. I honestly owe you my diploma. I couldn't ask for a better friend and colleague. Lastly, I would like to thank the George Mason University Department of Psychology for the immense amount of support I felt during the pursuit of my doctorate in clinical psychology.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

LIST OF ABBREVIATIONS

Ecological Momentary Assessment	EMA
Unconditioned Stimulus	UCS
Conditioned Stimulus	CS
Negative Affect	CS
Electroencephalogram	EMA
Hertz	hz
No-U-Turn	NUTS
Widely-Applicable Information Criterion	WAIC
Instrumental	Q
Inverse temperature	β
Outcome sensitivity	ρ
Positive learning rate	$\alpha_{positive}$
Negative learning rate	$\alpha_{negative}$
Go bias	b
Pavlovian bias	π
Value	V
Reinforcement	r

ABSTRACT

ANGER AND PAVLOVIAN BIAS: INTEGRATING LABORATORY TASK PERFORMANCE AND ECOLOGICAL MOMENTARY ASSESSMENT

Joseph A. Wonderlich, Ph.D.

George Mason University, 2020

Dissertation Director: Dr. Sarah Fischer Nowaczyk

The majority of human behaviors is goal-directed, meaning people act in a certain way to achieve a desired outcome. However, many symptoms of psychopathology are associated with impulsive behavioral choices inconsistent with an individual's goals. Research using laboratory tasks suggests this might be due to Pavlovian Bias, which can work against goal-orientated behavior. However, the extant literature on impulsive, maladaptive behaviors suggests that changes in affect highly impact impulsive behaviors. No research has examined the impact of mood on Pavlovian Bias. Thus, it is unknown whether changes in mood may impact one's ability to overcome Pavlovian bias. Additionally, given the nature of laboratory tasks, it's unclear whether these tasks have ecological validity. Therefore, the goal of this dissertation was to examine the impact of increased negative affect on Pavlovian bias and to examine if individual differences in various components of Pavlovian bias might moderate the trajectory of negative affect before and after an impulsive behavior in the real world. In Study 1, 30 individuals completed a

Pavlovian Bias task before and after an anger mood induction. Results from the task revealed that while anger induction did not change one's overall Pavlovian Bias score, individuals where more likely to make more mistakes in the Go to Avoid trials and to approach rewards after the mood induction. In Study 2, the same 30 individuals completed two-weeks of ecological momentary assessment (EMA), in which they responded to prompts assessing affect and impulsive behaviors several times a day. EMA data revealed negative mood significantly increased before and decreased after impulsive behaviors. Additionally, changes in the percent correct of Go to Avoid trials and reward sensitivity moderated the trajectory of negative affect before and after impulsive behaviors. Specifically, individuals who experienced a greater decrease in either their percent correct of Go to Avoid trials or reward sensitivity required less of an increase in negative affect before engaging in impulsive behavior. Findings from both of these studies suggest that acute changes in anger can impact one's ability to engage in goal-orientated behaviors that are rewarding, and approach driven. Furthermore, individual differences in task performance after an anger mood induction may impact the daily experience of negative affect and impulsive behaviors.

INTRODUCTION

Despite the fact that humans may anticipate negative outcomes from a behavior, they tend to make behavioral choices that are maladaptive. For example, people often choose to consume large quantities of alcohol, despite the fact that they may have experienced negative consequences from drinking in the past. Behavioral choices may be driven by two distinct systems: a goal-directed system and a habit-based system (Doll, Shohamy, & Daw, 2015; Voon et al., 2015). Goal-directed systems tend to use predictions about optimal outcomes to guide choices, and thus may be associated with more adaptive behavior (Doll et al., 2015). Habit-based systems tend to use information about previous rewards to guide behavior, and thus may influence engagement in more pathological, compulsive, or addictive processes (Voon et al., 2015). Two distinct models of instrumental learning (i.e., model-based and model-free) have been developed to describe the mechanisms through which goal-directed and habit-based behavioral choices are made. Pavlovian learning is learning in which an unconditioned stimulus (US) pairing with a conditioned stimulus (CS) leads to a conditioned response to the US (Braveman, 1979). Action tendencies (to approach or avoid) are influenced by Pavlovian learning, and Pavlovian bias may trigger behavior that conflicts with other valuation systems (Dayan & Berridge, 2014). Thus, one may have an adaptive long-term goal (reduce cholesterol), driven by instrumental learning. When presented with an appetitive cue (chocolate cake), that long term goal conflicts with Pavlovian conditioned responses.

Models of Instrumental Learning

Instrumental learning is the process in which an individual learns to differentiate rewarding actions from non-rewarding actions. To expand upon the goal-directed and habitual systems involved in instrumental learning, researchers using computational models have proposed two distinct mechanisms described as *model-free (habit)* and *model-based* (goal-directed) learning (Daw, Gershman, Seymour, Dayan, & Dolan, 2011; Daw, Niv, & Dayan, 2005; Gläscher, Daw, Dayan, & O'Doherty, 2010; Wunderlich, Dayan, & Dolan, 2012).

Model-based strategies require an individual to employ cognitive representation, or an internal map of events and stimuli from the external world, to generate goal-directed choices (Daw et al., 2005; A. Dickinson & Balleine, 2002). This cognitive representation, or internal model, allows the individual to assess the future consequences of their choices and actions. In this type of learning, individuals are thought to make a series of short-term predictions about the potential consequences of immediate future actions (Daw et al., 2005). In other words, individuals engage in more adaptive, goal-directed behavior when they use model-based learning. Model-based learning also has a distinct neurobiological pathway. Studies using electrophysiological (Holland & Gallagher, 2004; Pasupathy & Miller, 2005) and functional magnetic resonance imaging (fMRI; McClure, Laibson, Loewenstein, & Cohen, 2004) have demonstrated that the prefrontal cortex is closely associated with the evaluation of consequences associated with model-based learning.

In contrast, model-free learning does not rely on a cognitive representation of the outside world, but instead uses a “caching” system to store information about the value of consequences of past action. By caching information about past events, individuals inform their behavior based on predictions developed from repeated exposure to the valued outcomes. Model-free learning values can be described as being free-floating, since they can become detached from any specific outcome. Since they are not attached to future outcomes, they do not necessarily change with new information. Thus, model-free learning may be associated with habit-based, maladaptive behaviors associated with compulsive, addictive behavior patterns (Daw et al., 2005; V. Voon et al., 2015). Neuroimaging and electrophysiology studies have also identified a specific pathway for mode-free learning. These studies suggest that model-free learning is closely associated with the dopaminergic projection from the striatum (Collins & Frank, 2014). Pavlovian learning has long been assumed to be model free (Braveman, 1979; Dayan & Berridge, 2014).

Pavlovian Learning

Pavlovian bias may potentiate or antagonize instrumental learning. Pavlovian-Instrumental Transfer theory, or the belief that separate conditioning paradigms can be combined together to impact behavior, suggests that previously conditioned Pavlovian cues may enhance operant conditioning paradigms (e.g., instrumental learning) and yield greater response rates (Balleine & Killcross, 2006). To examine the effects of Pavlovian-instrumental transfer, it is required that the Pavlovian pairings and instrumental actions are conditioned in separate experimental phases. The instrumental actions are then tested in both the presence and the absence of the Pavlovian cues to assess the effect of the cues on the actions.

Pavlovian learning can also act in opposition to instrumental control (Dayan & Balleine, 2002). Pavlovian responses can be coupled with a stimulus and a certain valenced behavioral response (i.e., promoting approach behaviors with rewards and avoidance of punishment), and can even force action-outcome pairings that are suboptimal through Pavlovian-Instrumental transfer. Consequently, this suggests that Pavlovian learning can disrupt goal-oriented instrumental learning (M. Guitart-Masip et al., 2011; Hershberger, 1986). Interference in instrumental or reinforcement learning by Pavlovian conditioning may happen in several ways; one of which is the disruption of cognitive control. Individuals who exhibit a greater preference for Pavlovian control compared to instrumental control in certain situations are said to demonstrate a greater Pavlovian bias.

Pavlovian bias helps to explain why humans are more likely to learn to approach reward and avoid punishment, and why it is more difficult for many individuals learn not to act to obtain a reward and act to avoid a punishment. Several have explained that Pavlovian bias may be the cause of inflexible decision-making (Cavanagh, Eisenberg, Guitart-Masip, Huys, & Frank, 2013; Guitart-Masip, Duzel, Dolan, & Dayan, 2014). Specifically, they explain that the difficult of overcoming Pavlovian bias, and maintain goal-oriented behavior, is because individuals' innately associate stimuli predicting reward with approach-based behavior, while stimuli predicting punishments are prepotently coupled to withdraw behaviors. Thus, Pavlovian biases facilitate reward-based invigoration and punishment-based suppression.

Cognitive Control

While Pavlovian bias can be a strong influence on the way in which one behaves, it can also be overridden. Cavanaugh and colleagues (2013) suggest that one way in which instrumental learning might prevail over Pavlovian bias is by recruitment of an individual’s cognitive control capacity. Cognitive control, also referred to as an executive function, is the ability to voluntarily coordinate behavior in attempts to achieve internal goals. Successful cognitive control requires an individual to be cognitively flexible while maintaining focus on their goals and not becoming distracted by unrelated environment stimuli (Badre, 2011; Lenartowicz, Kalar, Congdon, & Poldrack, 2010; Sabb et al., 2008). Midfrontal theta has been associated with cognitive control to prevent impulsive responses (Cavanagh et al., 2011; Cohen, Schoene-Bake, Elger, & Weber, 2009). This signal, which is presumed to originate in the mid-cingulate cortex (Veen & Carter, 2002), may provide a mechanism through which striatal signals that drive Pavlovian approach behavior can be temporarily overcome. Studies using electroencephalogram (EEG) have demonstrated that cognitive control is reflected in midfrontal theta activity (ca. 4–7 Hz) (Cavanagh & Frank, 2014; Sauseng, Griesmayr, Freunberger, & Klimesch, 2010; Swart 2018(James F. Cavanagh, Zambrano-Vazquez, & Allen, 2012). (Griesmayr, Gruber, Klimesch, & Sauseng, 2010; Roberts, Hsieh, & Ranganath, 2013; Sauseng et al., 2010).). Changes in frontal midline (FM) theta power may reflect the amount of cognitive control processes required to resolve conflicts between Pavlovian and Instrumental control (Cavanaugh et al., 2013).

The Impact of Emotion on Cognitive Control and Cued Learning

Discrete emotions also impact an individual's motivation to engage in a goal-oriented behavior. Ekman's theory of basic emotions (Ekman, 1992) suggests that discrete emotions have unique autonomic response patterns and can initiate specific behavioral responses (Stephens, Christie, & Friedman, 2010). An early dimensional model of discrete emotions consists of two factors: emotional valence and emotional arousal (Morgan & Heise, 1988; Russell, Lewicka, & Niit, 1989). The valence dimension represents the degree to which an affective state is considered pleasant or unpleasant, while the arousal dimension captures the extent to which an individual reports feeling awake and alert or lethargic and drowsy (Posner, Russell, & Peterson, 2005; Russell et al., 1989). Multiple studies have found that discrete emotions can be reliably mapped onto dimensional states (Posner et al., 2009; Posner et. al., 2005; Russell et al., 1989). More recently, models of discrete emotions have added a third dimension, an "approach/withdraw" dimension of emotional experience. The approach/withdraw dimension is particularly relevant in discriminating negative emotions, such as anger and fear (both high in arousal and negatively valenced) from each other and is essential in understanding how emotions motivate certain behaviors (Carver & Harmon-Jones, 2009; Harmon-Jones & Harmon-Jones, 2010; Morgan & Heise, 1988). Additionally, the avoid/withdraw dimension explains how mood can influences behaviors and decisions in differentiated ways such that individuals are either more likely to interact with or avoid environmental stimuli when experiencing these emotions in heightened states (Carver & Harmon-Jones, 2009).

While negative affect is one of the strongest predictors of engagement in maladaptive, impulsive behaviors, it is unclear how negative affect might impact processes such as instrumental learning. Several studies using laboratory mood induction have demonstrated that when a person is experiencing heightened mood states, they are likely to express greater responsiveness to cues. For example, in a study of women with bulimia nervosa, the participants were asked to view a series of food cues before and after a negative mood induction. Once the participants were in a negative mood, they rated their cravings for food higher than before when viewing another series of food cues (Fischer et al., 2017). This work also demonstrated that the neurobiological response to food cues under increased distress moderated the relation between negative affect and binge eating behavior in the real world (Wonderlich et al., 2018a). Similar results were found for individual who frequently binge drank. These participants were asked to observed alcohol-related cues before and after a negative mood induction. They also endorse greater cravings and desire to drink alcohol while viewing alcohol-related cues after a mood induction (Rubonis et al., 1994; Stathopoulou, Pollack, & Otto, 2018). Ultimately, these studies suggest that negative mood may change the potency of a cue, although the cue itself may not change.

Additionally, some research suggests emotions themselves may become conditioned stimuli and elicit appetitive responses. Bongers & Jansen (2017) demonstrated that if an individual begins to associate specific mood states with consuming food, those specific mood states begin to elicit cued cravings and food selection. If both the cue potency is increased by emotions and the emotion itself can be a conditioned stimulus, it is possible that emotions might facilitate, or enhance, subsequent operant learning via Pavlovian-Instrumental Transfer.

Negative affect does not only impact the potency of a cue, but it can also impact one ability to engage inhibitory action through cognitive control. West, Choi, and Travers (2010) demonstrated that negative affect was associated with decreased neural correlates of cognitive control. Other studies have also demonstrated that cognitive control processes are vulnerable to modulation of emotional valence (Hammar & Årdal, 2009). One leading argument is that negative mood depletes individuals of their limited attentional resources (Ellis, Ashbrook, Fiedler, & Forgas, 1988). During states of negative mood, attentional resources may also be directed towards the effort of emotion regulation (Riediger, Wrzus, Schmiedek, & Wagner, 2011). Thus, this might suggest individuals experiencing increased negative affect might have more difficulty overriding their Pavlovian biases.

While no studies have examined the effect of acute changes in affect on Pavlovian bias, several recent experimental studies have demonstrated that acute stress and various forms of psychopathology associated with heightened long-term negative affect can impact cognitive control and Pavlovian bias. There is evidence that acute stress, history of trauma, learned helplessness, and depressive symptoms accentuate Pavlovian bias in experimental settings (Csifcsák, Melsæter, & Mittner, 2020; Mkrtchian, Aylward, Dayan, Roiser, & Robinson, 2017; Ousdal et al., 2018). One experimental study demonstrated that the increased Pavlovian bias was related to reduced cognitive control via the experience of learned helplessness (Csifcsák et al, 2020).

Lastly, Pavlovian bias can cause individuals to alter their behaviors or motivation, regardless of the information they have gathered through instrumental learning processes. Specifically, if a Pavlovian cue elicits approach motivation, an individual with high Pavlovian bias will be more likely to approach. Similarly, if the Pavlovian cue elicits an avoidance motivation, the individual will be more likely to avoid. Given Pavlovian bias incorporates its own approach/withdraw dimension, similar to newer models of discrete emotions, it is possible that specific discrete emotion might impact various component of Pavlovian bias differently. For example, anger, a facet of negative affect that is negative valence, highly arousing, and elicits approach-based motivations may have a greater impact on reward-based invigoration given that both anger and reward invigoration both share a similar approach dimension. Consequently, emotions like fear or sadness might impact punishment-based suppression given they all elicit withdraw or avoidant behaviors. Thus, it may be important to examine how discrete emotion may differentially affect various components of Pavlovian bias.

Summary

In summary, people make behavioral choices as a function of learning. Pavlovian conditioning is one pathway through which individuals associate stimuli with reward or punishment. Another pathway, instrumental learning, occurs via two different systems: a model-based or a model-free system. Both of these systems involve making decisions about a behavior based on cognition (either “caching” past rewarding value of a stimulus or making predictions about the future cost/benefit of a stimulus). Experimental studies have demonstrated that Pavlovian conditioning can complement or act in opposition to instrumental learning, but that this Pavlovian bias can be overcome by using top-down cognitive control. However, none of these experimental studies have examined the impact of acute emotions on the emergence of Pavlovian bias or the ability to use cognitive control to engage in model-based decision making. This is an important gap, as many compulsive or addictive behavior patterns are associated with acute negative emotional states and are driven by conditioning or model-free learning as opposed to model-based learning.

Thus, one of the primary goals of this dissertation project is to examine the impact of a discrete acute emotion on reinforcement learning. It is possible that reinforcement learning may be disrupted by the experience of acute emotion. If this happens, it may be due to an increase in Pavlovian bias because of the negative affect cue, or it could be due to a disruption in cognitive control. The second goal of this dissertation project is to examine how Pavlovian bias impact the momentary relation between negative affect and impulsive behaviors (e.g., binge eating, binge drinking, and aggressive behavior) in the natural environment.

PAPER 1:

The Impact of Anger on Pavlovian Bias and Instrumental Learning

The majority of human behaviors are thought to be goal-directed, meaning that most of the time people act in a certain way to achieve a desired outcome (Bandura, 1986). However, many symptoms of psychopathology are associated with behavioral choices that are inconsistent with an individual's goals. One hypothesis as to why this might occur is that behavioral decision making is strongly impacted by two parallel learning processes, which at times can work either with or against each another. Pavlovian learning involves the acquisition and storage of biologically potent information and the related actions. Specifically, Pavlovian learning promotes the association between cues (e.g., conditioned stimuli /unconditioned stimuli) which elicits certain behaviors. Instrumental learning is the process through which an individual learns to differentiate rewarding actions from non-rewarding actions. During instrumental learning, outcomes of behavior are learned and hypothesized to guide behavioral choices (Dickinson & Balleine, 2002). Pavlovian bias refers to persistence in engaging in approach or avoid behaviors which have been cue conditioned, and this process may influence compulsive maladaptive behavioral choices (Harb & Almeida, 2014).

Pavlovian and instrumental learning may influence each other. Instrumental learning has been broken down into two distinct forms described as *model-free* and *model-based.* Model-based strategies require an individual to use cognitive representation and evaluations of consequences from previous experiences to make goal-directed choices (Daw et al., 2005; A. Dickinson & Balleine, 2002). This model allows the individual to assess the future consequences of their choices and actions. Model-free learning, on the other hand, does not rely on predictions about future consequences of behavioral choices, but instead uses a “caching” system to store information about the value of consequences of past action. By caching information about past events, individuals inform their behavior simply based on previous outcomes. Experiments aimed to examine the model-based/model-free distinction have been highly fruitful (Daw et al., 2011; Gläscher et al., 2010; Wunderlich et al., 2012). For example, model-based mechanisms are thought to help produce cognitively flexible goal-directed behavior, whereas model-free mechanisms have often been treated as producing automatic, instrumental, stimulus-response habits (Daw et al., 2005). Pavlovian learning also contributes to behavioral choices. Pavlovian cues often elicit motivations to pursue and consume the rewards (or avoid the threats) with which they have been associated. For addicts and sufferers from compulsive urges, cue-triggered motivations may become quite powerful and maladaptive (Bushong et al., 2018).

Instrumental learning ensures that individuals are more likely to go after rewards and avoid punishments through consideration of the consequences (Dayan et al. 2006; Dayan & Daw, 2008). Pavlovian learning interacts with instrumental learning in several different ways. For example, Pavlovian learning may facilitate instrumental learning through a process called Pavlovian-instrumental transfer. Pavlovian-instrumental transfer occurs when separate conditioning paradigms are combined together to impact behavior. Combining previously conditioned Pavlovian cues may enhance operant conditioning paradigms (e.g. instrumental learning) and yield greater response rates. However, this process can also weaken the relationship between behaviors and rewards when conflicting action and valence requirements are paired (Dayan & Balleine, 2002). If such Pavlovian processes interfere with goal-oriented learning, it may lead an individual to make a behavioral decision that does not help them achieve their goal.

Although it is fairly easy for individuals to learn to approach reward and avoid punishment, they experience greater difficulties learning *not* to act to obtain a reward and *acting* to avoid a punishment. Stimuli predicting reward are intrinsically associated with behavioral approach, while stimuli predicting punishments are pre-potently coupled to behavioral inaction. Thus, through Pavlovian processes, certain cues can elicit behaviors that may be rewarding or punishing, and the behavior may persist under the influence of the cue. These pre-specified response tendencies are referred to as Pavlovian biases (Guitart-Masip et al. 2014). Pavlovian bias is thought to distort flexible instrumental decision making and has been associated with various forms of psychopathology (Voon, Lo, Ngui, & Ayob, 2011)

Pavlovian bias may be inhibited by cognitive control (Cavanagh et al., 2013). Cognitive control is the ability to voluntarily coordinate behavior in attempts to achieve goals. Cavanagh and colleagues designed a study to examine the impact of cognitive control on Pavlovian bias and recorded EEG signals to measure a neurobiological indicator of cognitive control while participants were performing the study tasks (Cavanagh et al., 2013). In this study, participants were conditioned to respond to cues with approach or avoid behaviors, and also had the opportunity to engage in instrumental learning. They obtained rewards or punishments for signaled approach or avoid responses. Thus, participants developed a Pavlovian bias towards specific cues, and then had to engage in instrumental learning to overcome the Pavlovian bias in responding in order to obtain rewards. Cavanaugh and colleagues hypothesized that cognitive control (e.g., as measured by EEG) provides a mechanism by which the signals that drive Pavlovian approach behavior could be temporarily overcome, ultimately preventing impulsive responses (Cohen et al., 2009; Cavanagh et al., 2011). Several studies utilizing neurobiological markers of executive function or cognitive control suggest that that cognitive control capabilities can inhibit impulsive responding due to Pavlovian bias/prior conditioning (Cavanangh and Frank, 2014; Csifcsak, Melsaeter, & Mittner, 2020).This suggests that individual differences in cognitive control can improve instrumental learning by overcoming Pavlovian bias.

Experimental studies of the impact of Pavlovian bias on instrumental learning have not considered the impact of acute emotion, specifically negative affect, on reinforcement learning. Although some studies suggest that individual differences in learned helplessness, overall stress, and exposure to trauma impact cue driven responses, very little experimental research has been published on the impact of an acute shift in emotion on these responses (Ousdal et al., 2018; Quail, Morris, & Balleine, 2017). Thus, although negative affect is one of the strongest predictors of engagement in maladaptive, impulsive behaviors (Simons, Dvorak, Batien, & Wray, 2010; Smyth et al., 2007; Swendsen et al., 2000) it is unclear how negative affect might impact instrumental learning or Pavlovian bias.

Negative Affect and Impulsive Behavior

Negative affect is a broad construct that encompasses many different discrete emotions (e.g., anger, depression, anxiety). In addition to the potential influence on cognitive control or executive functioning, discrete emotions have also been shown to impact an individual’s motivation to engage in a goal-oriented behavior (Berg et al., 2013). An early dimensional model of emotion posits that discrete emotions consist of 2 factors: emotional valence and emotional arousal (Morgan & Heise, 1988; Russell et al., 1989). Valence represents the degree of pleasantness or unpleasantness, while the arousal represents feeling either alert or drowsy (Russell et al., 1989).

Ekman’s theory of basic emotions (Ekman, 1992) suggests that discrete emotions have unique autonomic response patterns and can initiate specific behavioral responses (Stephens, Christie, & Friedman, 2010). Thus, some researchers have suggested that the two-dimensional emotional is not sufficient (e.g., Morgan & Heise, 1988). This research suggests that there is also an “approach/withdraw” dimension of emotional experience. This approach/withdraw dimension is particularly relevant in discriminating negative emotions, such as anger and fear (both high in arousal and negatively valenced) from each other and is essential in understanding how emotions motivate certain behaviors (Carver &Harmon-Jones, 2009; Harmon-Jones, E. & Harmon-Jones, C., 2010; Morgan & Heise, 1988).

Several studies suggest that acute negative affect might make it more difficult to override Pavlovian biases. For example, it is plausible that discrete emotions associated with negative affect may influence cognitive control. West, Choi, and Travers (2010) demonstrated that negative affect was associated with decreased neural correlates of cognitive control. Other studies have also demonstrated that cognitive control processes are vulnerable to modulation of emotional valence (Hammar & Ardal, 2009). One leading argument is that negative mood depletes individuals of their limited attentional resources (Ellis et al., 1988). During negative mood states, attentional resources may be directed towards the effort of emotion regulation (Riediger et al., 2011).

Additionally, given the motivational dimension of discrete emotions, it is possible that emotions might impact reinforcement. Both emotions and learning involve approach and avoidance, either due to unique biological markers of discrete emotions or reward evaluation involved in learning. Furthermore, some researchers have categorized Pavlovian bias as a linkage of affective states with action biases towards rewards or away from punishments (Albrecht, Waltz, Cavanagh, Frank, & Gold, 2016). This suggests that experiencing certain mood states, functioning as a Pavlovian stimulus, might change the relations between rewarding stimuli and approach-based actions, and the relations between punishing stimuli with avoidance-based behaviors. Specifically, it is possible that negatively valence moods that promote avoidances (e.g. sadness) might lessen the effect of other rewarding stimuli that would otherwise promote approach-based actions. Moreover, highly arousing emotions that motivate approach behaviors (e.g. happiness or anger) might enhance the effect of a reward.

Current Study

It is possible that the experience of acute negative affect may impact cognitive control abilities, and hence, disrupt model-based learning of adaptive behavioral responses. The aim of study 1 was to examine the impact of acute negative affect on instrumental, model-based learning in a laboratory-based task. In order to examine the potential impact of acute emotions on instrumental learning Pavlovian bias, we chose to modify the experimental paradigm used by Cavanaugh et al., (2013). In the current study, participants completed the task designed by Cavanaugh and colleagues to differentiate model-based learning and Pavlovian bias. However, after completing the task, participants undergo an anger mood induction. Then, participants completed the same task with drifted reinforcement to account for learning effects. Thus, the current study is designed to provide a within-person comparison of Pavlovian bias before and after an acute anger induction.

We chose to use anger in the current study for several reasons. Anger is a negatively valenced, highly arousing emotion that promotes approach behavior. These dimensions (negative valence and high arousal) are most commonly associated with impulsive behaviors (Becker, Fischer, Crosby, Engel, & Wonderlich, 2018). Though other emotions, like fear, are also highly arousing and negatively valenced, we chose anger because it is also associated with approach-based motivation, which overlaps with the motivational dimension associated with rewards. This is particularly important because Cavanguah et al., (2013) suggest that individuals prefer goal-orient, approach-based decision. If the motivational dimension of anger does indeed enhance the approach-based motivation of rewards, participants might exhibit a greater Pavlovian bias on the reward-based approach index of Pavlovian bias. [(“Go” responses on Go-to-Win + NoGo-to-Win)/ Total Go conditions].

Though the nature of these relations has never been tested within this paradigm, we have several hypotheses for this study: (1) after a negative mood induction, individuals will exhibit higher Pavlovian biases on the task (2) the anger mood induction will promote reward-based and approach parameters of Pavlovian biases, while not impacting the punishment and avoidances based parameters.

Methods

Recruitment and Inclusion and exclusion criteria

Participants were recruited from a large, Mid-Atlantic university undergraduate research subject pool. The goal of participant recruitment for the study was to recruit individuals who consumed at least 1 alcoholic drink per week. This requirement was put in place in order to ensure that the participants were likely to engage in at least one of the targeted behaviors of study 2 (described in the next section) during the time of the assessment. Inclusion criteria were: ≥ 1 alcoholic drinks either week, age 18–45 years, and able to use a ‘smartphone’. Exclusion criteria were: psychotic or neurological disorder, history of traumatic brain injury, and left-handedness. A total of 431 people responded to study initial advertisements, with only 237 meeting the inclusion criteria. Of the 237, only 136 completed the full baseline assessment. All 136 participants were invited to the next stage of the study, but only 35 agreed to come to a laboratory task session. All 35 completed the task, but 5 individuals were removed from the study due to irregularities in the data.

Procedure

Participants first completed an online pre-screen and baseline assessment. As part of the baseline assessment, participants were asked to write a brief narrative about the time they felt angriest. Eligible participants then completed the laboratory task session at the George Mason University. Upon arrival to the task session, participants were consented and asked to rate their baseline levels of distress via an affect grid. Next, participants were informed they would complete a task in which they could either respond to a target (“Go”) or they could withhold a response (“NoGo”). Additionally, they were told that each cue would lead to a reward, a neutral response, or a punishment based on their responses and that they should explore both response options in order to learn how to achieve the best outcome from each cue. Before beginning the first run of the task, the participants were again asked to rate their level of distress on an affect grid. Following the first run, participants complete another affect grid. Participant were then read the narrative they wrote during the baseline assessment about the time they were the angriest. This served as a negative mood induction. Immediately after hearing the narrative, participants completed another affect grid and began run 2.

Materials

Assessments and measures.

Affect Grid (Russel et al., 1989). Valence and arousal were measured using the Affect Grid. This instrument asks subjects to rate their feelings by placing an “X” in the position within a 9 × 9 matrix that best reflects their emotional states along the pleasant/unpleasant (horizontal) and arousal (vertical) dimensions (both scored numerically from 1 to 9). See Figure 1. for a detailed view of the affect grid.

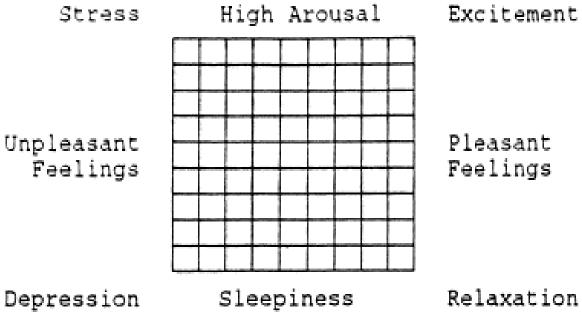

Figure 1. The affect grid as seen by participants.

Pavlovian Learning Task. The learning task was adapted by Cavanaugh and colleagues (2013) from a task previously used by Guitart-Masip et al. (2011). This task is a modified go/no-go task that has orthogonalized action and valence to distinguish Pavlovian bias and model-based (instrumental) learning.

Each trial of the task consisted of three events: a cue, a symbol to represent when the participant should engage their action choice (Go or NoGo), and an outcome. Participants were told that they could either respond to the target ("Go") or they could withhold a response ("NoGo"). They were also told that each cue would lead to a reward, a neutral response or punishment based on their responses and that they should explore both response options to best learn how to achieve the best outcome from each cue. There were four action-reward combinations: Go-to-Win, Go-To-Avoid, NoGo To-Win, and

NoGo-to-Avoid. Both the Go-to-Win and the NoGo-to-Avoid conditions are considered to be Pavlovian congruent, while Go-To-Avoid and NoGo To-Win are both considered Pavlovian conflict conditions. Each combination was presented 30 times across 12 blocks with a break between.

Each trial began with the display of a colored shape cue. Next, the participants saw the target indicating they should make a decision about which action to choose. In Run 1, there was an 80% chance each cue was predictive of the correct action to take (Go or NoGo) to gain the optimal outcome (reward or avoid punishment), whereas 20% of incorrect actions were reinforced. Next, the participants saw the target indicating they should make a decision about which action they should choose. The target disappears if participants pressed the button to indicate they have selected the “Go” option, or after 1000 ms. Next, the participants were provided feedback indicating reward, neutral response, or punishment (green $ to indicate a win, a red $ to indicate a loss, or yellow equals sign to indicate no reward or punishment). Participants then completed the task a second time. However, to ensure there are no learning effects across the two runs, the shapes and colors were changed, and the percent chance of a correct action-reward combination was drifted from 80% to 70%. After finishing both runs of the task, participants were paid up to $40 depending on the amount they won during the task.

A Pavlovian bias score is estimated by creating a reward-based approach index and punishment-based avoidance index. For the reward-based approach index, all “Go” responses on both the Go-to-Win and the NoGo-to-Win trials are added together and divided by the total number of Go responses [(“Go” responses on Go-to-Win + NoGo-to-

Win)/ Total Go conditions]. This calculation provided an estimation of how often someone engaged in a previously conditioned response (pressing “go”), even when a new response would have been more adaptive. The same calculation was made for punishment-based responses. These two indices were then averaged into a single metric, which is called Pavlovian Performance Bias. This metric represented an index of how likely a participant was to engage in previously conditioned responses, despite receiving outcomes on the task that could have been incorporated into predictions about how to respond more adaptively in order to win money. By averaging the reward-based approach and the punishment-based avoidance indices, this metric accounts for two comparable, but distinct types of Pavlovian conflict.

*Narrative Negative Mood Induction***.** Participants were asked to write down and describe in detail the time they remember being the angriest. When the narrative was read back to them at a later date, they were asked to image reliving the experience that made them angry with vivid detail. This methodology has been used induce a targeted affective state in various laboratory settings (Bodenhausen, Sheppard, & Kramer, 1994; Brinol, Petty, Valle, Rucker, & Becerra, 2007; Goodwin & Williams, 1982; Jefferies, Smilek, Eich, & Enns, 2008).

Data Analysis Plan

In order to better understand the effect of anger on Pavlovian bias and overall instrumental learning, we first calculated the percent correct for each trial condition. This allowed us to calculate the reward-invigoration and punishment-suppression indices for both run 1 and run 2 of the task. Next, both pre-mood induction indices were combined to create of index of Pavlovian bias score for each participant for run 1. The same procedure was used to calculate a Pavlovian bias score for run 2 using the post-mood induction reward-invigoration and punishment suppression indices. Second, after we calculated the Pavlovian bias from both run 1 and run 2, we conducted a three way within subjects ANOVA. The purpose of the ANOVA was to determine the individual and combined effects of action choices, outcome valence, and mood state on the overall percentage of correct responses. Third, we used stepwise computation modeling in order to understand the influence of Pavlovian bias on each participant's instrumental learning. Each step of the analyses plan will be described more detail in the following sections.

Pavlovian Bias Score. To calculate the amount of Pavlovian biases each participant experienced during the task, similar methods used by Cavanaugh and colleagues (2013) were used as a metric to gauge reinforcement responsiveness. As approach and avoidance conditions do not motivate individuals to engage in action the same way, two distinct outcome-action indices were analyzed, which will then be combined into an overall metric of Pavlovian Performance Bias. For the reward-based approach index, all "Go" responses on both the Go-to-Win and the NoGo-to-Win trials were added together and divided by the total number of Go responses [("Go" responses on Go-to-Win + NoGo-to-Win)/ Total Go conditions]. For the punishment-based avoidance index, all NoGo responses on both the Go-to-Avoid and the NoGo-to-Avoid trials were divided by the total NoGo responses [("NoGo" response on NoGo-to-Avoid + Go-to-Avoid)/Total NoGo conditions]. These two indices will then be averaged into a single metric of Pavlovian Performance Bias. By averaging the reward-based approach and the punishment-based avoidance indices, this metric accounts for two comparable, but distinct instrumental outcome-action pairings.

Perfect learning of the task results in a 50% Pavlovian Performance Bias because half of the trials included in each outcome-action measure are Pavlovian congruent conditions (i.e., Go-to-Win and the NoGo-to-Avoid), while the other half are Pavlovian conflict conditions (i.e., NoGo-to-Win and the Go-to-Avoid). Thus, greater reliance on Pavlovian Bias is reflected by higher scores on this metric. These scores were calculated for both run 1 and run 2 separately. Paired sample t-tests were used to compare Pavlovian Performance bias from the pre-mood induction run to the post-mood induction run, as well as comparisons of the indices of reward-invigoration, punishment suppression, and percent correct on all four trials of the task.

A three-factor ANOVA was used to examine the effect of Action (Go vs No-Go), Outcome (Win vs Avoid), and Timepoint (Run 1 vs Run 2) on the percent correct of all the trials. The use of a 2x2x2 ANOVA, allowed us to examine (1) if there is a difference in whether or not an individual is more likely to Go vs No-Go within each run (2) if reward or punishment cues are more likely to elicit a correct response within each run, and (3) if there is an overall difference in performance from time 1 to time 2. This analysis also indicates whether or not there was a statistically significant decrease in the percentage of correct responses from time 1 to time 2 on specific action x outcome combinations (Go to Win, Go to Avoid, NoGo to Win, and NoGo to Avoid). All three factors were within-subject repeated measures. Tukey's HSD test was used for post hoc tests. Effects with $p < 0.05$ were considered statistically significant.

Computational Modeling. In additionally to the ANOVA, we used Bayesian hierarchical modeling and stepwise model comparison to examine the mechanism by which Pavlovian bias influences choice behavior in the Go/No-Go tasks, and to determine the nature of the relations among various parameters of reinforcement learning (RL) and Pavlovian bias. Computational modeling allows us to examine latent parameters thought to underlie individual differences in behavioral performance (Guitart-Masip et al., 2012) and the degree to which these parameters were modified as a function Pavlovian bias. Separate RL models were fit for the both runs of Go/No-Go tasks. We adapted a series of existing computational models of this task (Guitart-Masip et al., 2012; Cavanagh et al., 2013) to estimate parameters that underlie Pavlovian-Instrumental interactions during RL. Progressively more complex models were fit to trial-by-trial behavioral data using hierarchical Bayesian model fitting implemented in Stan (Carpenter et al., 2016), and models were compared by examining if they explained additional variance (penalized for additional parameters). Specifically, stepwise inclusion of the various parameters examines the likelihood each parameter explains individuals' overall learning or performance.

Performance on the Go/No-Go tasks was first modeled as an Instrumental (*Q)* learning process with state-action (Q) values updated on a trial-by-trial basis using a Q-learning algorithm:

For reward trials:

$$Q_t(a_t|s_t) = Q_{t-1}(a_t|s_t) + \alpha_{positive}\left(\rho * r_t - Q_{t-1}(a_t|s_t)\right)$$

Equation 1. Q model for reward trials

For punishment trials

$$Q_t(a_t|s_t) = Q_{t-1}(a_t|s_t) + \alpha_{negative}\left(\rho * r_t - Q_{t-1}(a_t|s_t)\right)$$

Equation 2. Q model for punishment trials

where reinforcements (r) come from the set $r \in (-1,01)$, ρ is a free parameter accounting for outcome sensitivity, and $\alpha_{positive}$and $\alpha_{negative}$ are free parameter accounting for learning rate, bound between 0 and 1. The learning rate represents how well an individual learns the instrumental contingencies of the task. An alternative model with one learning rate and valenced outcome sensitivities was also tested but the WAIC for this model was poorer that the valenced learning rate, single outcome sensitivity model, as was also reported by Moutoussis et al 2018. To account for the bias to Go, or the prepotent tendency to go rather than avoid regardless of the cue, a second model included an additional free parameter *(b)* on Go trials:

$$Q_t(Go|s_t) = Q_t(Go|s_t) + b$$

Equation 3. Q learning + Go bias model

To model the influence of Pavlovian bias, or the tendency to approach rewards and avoid punishments, we modeled value of each stimulus as a static value (0.5 for stimuli that predict rewards, and -0.5 for stimuli that predict punishment. We tried a model in which we estimated the learned value of each stimulus as a function of reward history:

$$V_t(S_t) = V_{t-1}(S_t) + \alpha\big(r_t - V_{t-1}(S_t)\big)$$

However, the WAIC of this model was greater than the model with static Pavlovian value, as was also found by Swart et al., (2018). The value of each stimulus was then added to bias the state-action value for Go responses:

$$Q_t(Go|s_t) = Q_t(Go|s_t) + b + \pi * V_t$$

Equation 4. Q learning + Go bias + Pavlovian bias

where π is free parameter representing the strength of Pavlovian bias and $V \in (-0.5{,}0.5)$.

The full M3 model was therefore:

if s_t = Go To Win or NoGo To Win:

$$Q_t(a_t|s_t) = Q_{t-1}(a_t|s_t) + \alpha_{positive}\big(\rho * r_t - Q_{t-1}(a_t|s_t)\big) + b + \pi * V_t(0.5)$$
if $a = Go$ and $r_t \in (01)$

$$Q_t(a_t|s_t) = Q_{t-1}(a_t|s_t) + \alpha_{positive}\big(\rho * r_t - Q_{t-1}(a_t|s_t)\big)$$
if $a_t = NoGo$ and $r_t \in (0{,}1)$

ifs_t = Go To Avoid or NoGo To Avoid:

$$Q_t(a_t|s_t) = Q_{t-1}(a_t|s_t) + \alpha_{negative}\big(\rho * r_t - Q_{t-1}(a_t|s_t)\big) + b + \pi * V_t(-0.5)$$
if$a_t = Go$ and $r_t \in (-1{,}0)$

$$Q_t(a_t|s_t) = Q_{t-1}(a_t|s_t) + \alpha_{negative}\big(\rho * r_t - Q_{t-1}(a_t|s_t)\big)$$
if$a_t = NoGo$ and $r_t \in (-1{,}0)$

Equation 5. Full Model

The Q values were used to control the choice probability of action according to a softmax rule:

$$p(a|s) = exp\frac{(Q(a_t|s_t) * \beta)}{\sum exp(Q(a|s) * \beta)}$$

where β is an “inverse temperature” parameter that reflects the degree to which the probability reflects the highest value action. Bayesian hierarchical modeling was used to estimate the joint posterior distribution of parameters for the models, conditional on all participant choices and rewards. The No-U-Turn (NUTS) sampler implemented in Stan was used to estimate posterior distributions of parameters. We ran two chains of 2000 samples each, discarding the first 1000 samples as burn-in. All of the free parameters were treated as random effects. Models were compared using the Widely-Applicable Information Criterion (WAIC; Watanabe, 2013) where lower values means better model fit. Separate posterior distributions of parameters were modeled for run 1 and run 2 of the tasks. Weakly informative priors were used: priors for parameters with infinite support (β, b, π, ρ) were Gaussian *N*(0,10) for means, *Cauchy* (0, 2) for standard deviation; for parameters bound between [0,1] ($\alpha_{positive}$, $\alpha_{negative}$) priors were drawn from *Beta* (A,B) distributions, with A and B transformed from M=A/(A+B) and S= 1/sqrt(A+B), with M drawn from a uniform distribution *U* (0,1) and S drawn from uniform distribution U (0, Inf).

Results

Mood Induction

A series of paired samples t-tests of the data from the affect grids before and after the anger mood induction revealed a significant increase in arousal from run 1 (M = 4.83, SD = 1.659) to run 2 (M = 5.89, SD = 2.007) (t (29)= 2.62, p = 0.013). Additionally, there was a significant decrease in valence from run 1 (M = 5.91, SD = 1.772) to run 2 (M = 3.66, SD = 1.522) (t (29) = -6.26, p < 0.000). These results suggest that the mood induction sufficiently increased arousal and decreased valence as would be expected of an angry mood.

Task Performance

To better interpret task performance before and after a mood induction, we performed a three-way within subjects ANOVA of the percent of correct trials, incorporating factors: action (Go/No-Go) × Outcome (Win/Avoid) × Timepoint (Pre/Post mood induction). The result of the ANOVA reveals a significant main effect for action F(1,30) = 7.36, p = 0.01), a significant main effect of time (F(1,30) = 12.36, p < 0.000), but no main effect of outcome (F(1,30) = 3.09, p = 0.81). However, these effects must be interpreted within the context of a significant action by outcome interaction (F(1,30) = 31.97, p < 0.000). Thus, the behavioral data from the task indicate that while subjects were equally good at learning from rewards and punishments, they showed better performance in conditions requiring a go choice than in trials requiring a no-go choice and performed worse overall following the mood induction. Additionally, participants were better in the go to win condition (compared to go to avoid condition) and were better at learning to withhold a response (no-go) in the punishment condition (compared to a similar response in the reward condition).

To further examine the effects of the mood induction, Pair-Samples T-tests were conducted on all individual trials pre- and post-anger induction. The result of the paired-samples t-test showed that only the Go to Avoid condition significantly decreased from Run 1 (M = 0.65, SD = 0.22) to Run 2 (M = 0.59, SD = 0.24) following the mood induction; t(29) = 2.208, p = 0.034.

Computational Modeling

The stepwise addition of parameters in each model M1–M3 yielded increasingly better fits, as measured by WAIC. Specifically, we found that relative to a Q-learning (M1) and the Q-learning + Go (M2) models, including a Pavlovian bias parameter (π) increased model fit of M3 considerably for both the pre- and post-mood induction trial of the Go/No-Go task (see Table 1.)

Table 1. Widely Applicable Information Criterion (WAIC) for the different computational from the pre- and post-anger mood runs of the task

	Pre-Anger Mood Induction	Post-Anger Mood Induction
Model	WAIC	WAIC
M1: Q	4.633e+03	4.597e+03
M2: Q + Go	3.886e+03	3.893e+03
M3: Q + Go + Pav	3.761e+03	3.720e+03

In the winning model for both pre-and post-mood induction runs (M3), group level results showed that the both positive ($\alpha_{positive}$) and negative learning rates ($\alpha_{negative}$) were > 0 for the entire sample. This suggest that participants did in fact learn the instrumental contingencies of the task. Next, reward sensitivity estimates (ρ) were positive at the group level (100% group-level samples > 0), indicating that the rewards or punishments of the task did indeed impact instrumental behavior. Similarly, Pavlovian bias estimates (π) were positive (100% group-level samples > 0), meaning "win" cues did in fact elicited Go responding while "avoid" cues suppressed Go responding. Group-level parameters, and plots of posterior means of individual-level parameter estimates, of the winning model for the pre- and post-anger mood induction trials of the Go/No-Go tasks are presented in Figure 2.

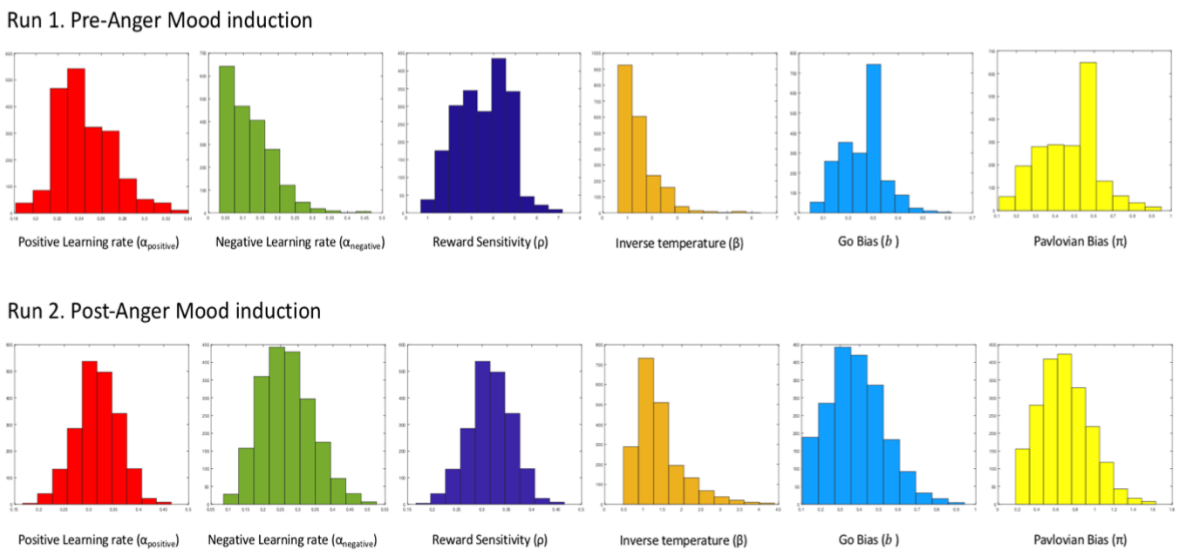

*Figure 2***.** Posterior distributions of model parameters from the M4a model from the pre-anger induction (top row) and post-anger induction (bottom row) tasks. Histograms represent posterior distribution of HMC samples (n = 2000) of the group-level parameters.

Paired-samples t-test of the parameters of the models from the pre- and post-anger mood induction revealed a significant increase in positive learning rate from run 1 (M = 0.24, SD = 0.031) to run 2 (M = 0.39, SD = 0.11) (t (29) = 3.22, p = 0.003). Additionally, there was a significant increase in negative learning rate from time 1 (M = 0.08, SD = 0.10) to time 2 (M = 0.25, SD = 0.337) (t (29) = 2.36, p = 0.025). Taken together, these results suggest that individuals are more likely to learn the instrumental contingencies of the task once they are in an angry mood. There was also an increase in the Go bias *(b)* parameter from run 1 (M = 0.26, SD = 0.12) to run 2 (M = 0.36, SD = 0.06) (t (29) = 5.10, p < 0.000), meaning that individuals were more likely to have a bias to Go, or approach, regardless of the cue once in an angry mood. Finally, there was a significant increase in the Pavlovian bias parameter from run 1 (M = 0.48, SD = 0.04) to t run 2 (M = 0.66, SD = 0.07) (t (29) = 12.132, p < 0.000). This indicates that once an individual was in an angry mood, “win” cues were more likely to promoted Go responding while “avoid” cues were more likely to suppressed Go responding compared to performance in run 1.

Discussion

To date, no studies have examined how acute changes in mood impact Pavlovian bias. The goal of this study was to examine how induction of anger, a negative-valence, high arousal, and approach-based emotion could impact an individuals’ performance on a task designed to assess Pavlovian bias. These analyses yielded several novel findings. First, results from the task performance indicated that not all of the trials were equally impacted by the anger induction. Specifically, while participants were equally good at learning from both rewards and punishments, they showed better performance in conditions requiring a go choice than in trials requiring a no-go choice. Also, when comparing the pre- and post-anger mood induction, performance on the task was worse overall following the mood induction. Finally, a significant two-way interaction between the action and outcome of the trial suggests that participants were better in the go to win condition (compared to go to avoid condition) and were better at learning to withhold a response (no-go) in the punishment condition (compared to a similar response in the reward condition). Had these findings fully supported our hypotheses, we would have expected to see an even further increase in performance of Go-to-Win trials at time 2 compared to time 1. Pre-to post-anger mood induction comparisons indicated that only the percent of correct responding to Go to Avoid (Pavlovian incongruent) condition decreased following the mood induction.

Results from the stepwise computational modeling analyses revealed that the best fitting model included a Pavlovian bias parameter (π) in additional to the typical Q-learning (M1) and the Q-learning + Go bias models for both the pre- and post-mood induction trial of the Go/No-Go task. Additionally, the analyses reveal that: (1) individuals did indeed learn the instrumental contingencies of the task, (2) the rewards or punishments of the task did indeed impact instrumental behavior, and (3) "win" cues did elicit Go responding while "avoid" cues suppressed Go responding, due to a Pavlovian bias.

Pre- and post-angry mood comparisons of the model parameters revealed a significant increase in positive and negative learning rate from time 1 to time 2, suggesting that individuals are more likely to learn the instrumental contingencies of the task once they are in an angry mood. There was also an increase in the Go bias (*b)* parameter following the anger induction, meaning that individuals are more likely to have a bias to Go, or approach, regardless of the task conditions, once in an angry mood. Finally, there was a significant increase in the Pavlovian bias parameter suggesting that once an individual was in an angry mood, "win" cues were more likely to promoted Go responding while "avoid" cues were more likely to suppressed Go responding. These results indicate that acute changes in anger do impact the ability for individuals to engage in goal-oriented behaviors.

Taken together, these results indicate that individuals are able to learn the task more quickly following an anger mood induction but are at risk to make more mistakes due to an increased likelihood of approaching (i.e., or responding "Go") to all cues, which ultimately increased their Pavlovian bias. This pattern of results may be explained by considering the dimensional model of anger (highly arousing, negatively valenced, and approach-based). While it is possible that the observed increased learning rate is result of the novelty of the mechanics of the task wearing off by the second run, it could also be that the increased arousal, or attentiveness, from the anger mood induction increased one's ability to learn the task. Nielson and Powless (2007) suggest that arousal plays important roles in encoding and attention for an event. Specifically, they suggest that increases in emotional arousal, regardless of valence, significantly enhanced delayed memory retrieval. Thus, increased arousal may help the participants to learn the task quicker by having an increased ability to recall the outcomes associated with the previous cues. However, the approach dimension of anger may provide insight as to why individuals learn the task more quickly, but made more mistake following the anger induction. The desire to approach from the anger mood induction appears to have enhanced the prepotent "Go" bias (or approach bias), ultimately resulting in more mistakes and increasing overall Pavlovian bias from time 1 to time 2.

Whiles this study provides novel, and potentially important findings of the impact of mood on reinforcement learning, there are several limitations. First, and most importantly, given that we did not account for cognitive control in our modeling, it is unclear whether or not anger impacted Pavlovian bias directly versus anger may have impacted an individual’s ability to recruit cognitive control abilities. Thus, the potential mechanism by which anger impacts reinforcement learning is unclear. Second, while we did have a good fitting model in our computational modeling analyses, it is impossible to test all potential models. Therefore, it is possible that there is a better fitting model for our data. Third, most of the participants were young Caucasian women, thus, our results may not generalize across ethnic groups, gender, or age. Future research might profitably evaluate differential effects across these and other variables. Finally, while it appears that anger did in fact impact reinforcement learning by increase and individuals Go bias and reinforcing prepotent conditional Pavlovian responses, we cannot make inferences about how other discrete emotions, or negative affect in general, may impact reinforcement learning.

Despite these limitations, there are several important implications of these findings. These results suggest that individuals struggle with goal-orientation when there is an acute change to their mood. Consequently, interventions aimed at helping people achieving their goals may want to incorporate distress tolerance and emotion regulation to help diminish the effects of stimuli that produce effects that might be in direct opposition to the ultimate goals. Additionally, these results highlight the further need for more ecologically sensitive methodologies of behavioral choices that incorporates the role of affect, Pavlovian cues, and cognitive control, as well as individual difference variables, on goal-directed decision making.

PAPER 2:

The Momentary Relation between Anger, Impulsive Behaviors, and Pavlovian Bias

Despite anticipating negative outcomes from certain behaviors, people tend to make behavioral choices that are maladaptive. For example, people often choose to eat food that is high in sugar or consume large quantities of alcohol, despite the fact that they may have experienced negative consequences from these behaviors in the past. These examples highlight paradoxical, and potentially destructive, characteristics of behavioral choices associated with various forms of psychopathology. Understanding both the cognitive and motivational systems of decision making might help to identify potential mechanisms of such psychopathology. Thus, an important question to ask about these inconsistent choices is why people continue to make maladaptive choices if the outcome is not likely to be favorable. One factor that influences maladaptive behavioral choices is the experience of negative affect.

Negative Affect and Impulsive Behavior

Several studies of impulsive or compulsive behavior patterns indicate that acute negative affect is an antecedent to these choices. Binge eating (i.e., eating an objectively large amount of food in a short period of time while experiencing a loss of control), problem drinking, aggression, and other behaviors are often influenced by acute negative affect. Studies of these behaviors utilizing ecological momentary assessment (EMA) are particularly compelling, as this data occurs in the participant's natural environment in “real time.” Researchers using EMA have shown that negative affect (NA) increases and positive affect (PA) decreases before binge type behaviors, while NA decreases and PA increases following binging (Berg et al., 2013; Smyth et al., 2007). Shiffman and Waters (2004) also demonstrated for people who are trying to quit smoking, there was a steady increase in negative affect for the 6 –7 hours preceding lapses. Using similar methodology, Kranzler, Armeli, Feinn, and Tennen (2004) demonstrated that heavy drinkers drank alcohol following increasing negative affect.

Instrumental Learning, Pavlovian Bias, and Impulsive Behavior

A large body of research has indicated that all behavioral choices (either adaptive or maladaptive) are informed by two orthogonal learning processes, instrumental and Pavlovian learning. Instrumental learning is the process in which an individual learns to differentiate rewarding actions from non-rewarding actions. Instrumental learning occurs via two different systems: a model-based or a model-free system (Daw et al., 2005). Model-based instrumental learning relies on making predictions about the future cost/benefit of a reward, while model-free instrumental learning uses a caching system to guide decisions, which stores information about the past rewarding value of a stimulus. Alternatively, Pavlovian conditioning is another pathway through which individuals learn to associate particular stimuli with the rewarding or punishing consequences of their behaviors.

Experimental studies have demonstrated that Pavlovian conditioning can complement or act in opposition to instrumental learning (Dayan and Balleine, 2002). Specifically, Pavlovian learning can impair instrumental learning by stifling the pairing of conflicting action and valence requirements. If such Pavlovian processes interfere with goal-oriented learning, it might lead an individual to make a behavioral decision that does not help them achieve their goal. Additionally, it is thought that these goal-oriented decision-making failures might be associated with various forms of psychopathology. Several studies have suggested that Pavlovian cues, or stimuli that have acquired the ability to elicit specific biological responses, are closely associated with binge eating and drugs abuse, even when an individual is trying to abstain from these behaviors (Caggiula et al., 2001; Chaudhri et al., 2007).

Cavanagh and colleagues (2013) suggested that maladaptive Pavlovian biases, which could cause an individual to fail to consider the consequences of their behavior choices, might be inhibited by cognitive control. Cognitive control is the ability to voluntarily coordinate behavior in attempts to achieve goals. Successful cognitive control requires an individual to be cognitively flexible while maintaining focus on their goals and not becoming distracted by unrelated environment stimuli (Badre, 2011; Miyake et al., 2000). Cavanagh et al. (2013) showed with event-related potential (ERP) recordings that midfrontal theta power, a neurobiological indicator of cognitive control, was associated with successfully overcoming a Pavlovian bias during modified go/no-go task which orthogonalized action and valence. Given impulsive behaviors have been conceptualized as emerging from basic deficits in cognitive control (Enticott, Ogloff, & Bradshaw, 2008; Evenden, 1999; Nigg, 2001) the findings by Cavanagh et al. (2013) might suggest that individuals who are more prone to Pavlovian bias are more susceptible to engaging in maladaptive, impulsive behaviors.

However, no studies have examined the impact of acute emotions on the emergence of Pavlovian bias in model-based decision making. This is an important gap, as many compulsive or addictive behavior patterns are associated with acute negative emotional states and are driven by cued conditioning or model-free learning as opposed to model-based learning. For example, binge eating is thought to be a negatively reinforced behavior (Heatherton & Baumeister, 1991; Pearson, Wonderlich, & Smith, 2015). Individuals may binge eat to distract themselves from aversive self-related cognitions or negative emotions. Thus, negative affect is temporarily reduced during binge eating, and occurs repeatedly, despite having multiple negative consequences. Similar theories have been put forward for alcohol dependence, drinking problems (Coskunpinar, Dir, & Cyders, 2013), intimate partner violence perpetration, and aggression (Derefinko, DeWall, Metze, Walsh, & Lynam, 2011; Scott, DiLillo, Maldonado, & Watkins, 2015).

We attempted to demonstrate in study one that negative affect, specifically the facet of anger (highly arousing, negative valenced, and approach based), could impact the relationship between instrumental learning and Pavlovian learning. The findings from Study 1 suggest that acute increase in anger decreased an individual's performance on Pavlovian incongruent trials (Go to Avoid) and increased one's prepotent conditioning to approach rewards (i.e., increased reward-invigoration). Additionally, the result from the Bayesian computation modeling indicated that following an anger mood induction, there was an increase in individual's learning rate (i.e., how well they learn the instrumental contingencies of the task), and increase in a bias to Go compared to Avoid, and an increase in the impact Pavlovian bias has on reinforcement learning. However, all studies of Pavlovian bias have occurred in a highly- controlled laboratory setting. It has yet to be established whether there is a link between data gathered during tasks assessing Pavlovian performance bias and the daily experience of impulsive behaviors that might occur as a result of Pavlovian conditioning.

Thus, the current study aims to integrate ecological momentary assessment (EMA) with the task-based performance data collected in study 1. The goal of study 2 is to explore how individual differences in changes in various components of instrumental learning and Pavlovian bias interact with shifts in negative affect in daily life to impact behavior in an ecologically valid setting (Wilson, Smyth, & Maclean, 2013). Previous studies have successfully integrated EMA data with individual differences in neural correlates of a task measured via fMRI, and have demonstrated that these individual differences can impact the real-time relation between well-known predictors of impulsive behavior (e.g. stress, negative affect, craving) and the impulsive behavior itself (Fischer et al., 2017; Wonderlich et al., 2017; Wonderlich et al., 2018). However, no study has used the same approach to integrate data representing Pavlovian bias and EMA.

Current Study

In this study, we examined how individual differences in aspects of Pavlovian bias (e.g., overall change in Pavlovian bias score, change in computation model fit parameters [learning rate, reward sensitivity, Go bias, Pavlovian bias] , and change in both incongruent and congruent trials) pre to post anger induction may impact the relation between the trajectory of negative affect and anger before and after impulsive behaviors. With regard to our target behavior, we believed creating a composite of impulsive, approach-based behaviors (e.g., binge eating, binge drinking, aggression) would allow us to examine whether or not Pavlovian bias is transdiagnostic mechanisms. We also plan to look at both a composite of negative affect and anger separately.

Based on the findings from study 1and previous studies using EMA to examine the relation between NA and individual impulsive behaviors like binge eating or alcohol consumption, I hypothesize that: (1) NA will increase prior to impulsive behaviors and decrease following the impulsive behavior (2) Individuals with greater decreases in one or all of the components of reinforcement learning and Pavlovian bias (overall change in Pavlovian bias score, change in the individual computation model parameters, and change in both congruent and incongruent trials) after a mood induction will experience less of an increase in negative affect before impulsive behaviors. The reason for this hypothesis is that if anger interacts with the approach dimension of Pavlovian bias or decreases cognitive control, it would suggest that the individual would be less likely to tolerate increases in negative affect and would be more likely engage in impulsive behaviors more quickly. If cues for a person are increasing in potency when they experience negative mood, it is less likely that people are able to overcome the desire elicited by the cue and will give in to the temptation more readily than enduring prolonged exposure to negative affect.

Methods

Inclusion and exclusion criteria

Participant recruitment and participation have previously been described in study 1. To review, participants were recruited from a George Mason University's undergraduate research subject pool. The goal of participant recruitment for the study was to recruit individuals who consumed at least 1 alcoholic drink per week to ensure that the participants were likely to engage in at least of the targeted behaviors during the time of the assessment. Inclusion criteria were: ≥ 2 alcoholic drinks either week, age 18–45 years, and able to use a 'smartphone'. Exclusion criteria were: psychotic or neurological disorder, history of traumatic brain injury, and left- handedness. Additional inclusion criteria for Study 2 required that all participants have completed the laboratory task described in Study 1.

Participants

Participants were 35 individuals (female = 23 and male = 12) who completed the experimental laboratory tasks. Of the 35 participants, 5 were removed due to incomplete data capture during the laboratory task session. The final sample included 30 participants (19 female). Of the remaining participants 53.3% (16) described themselves as Caucasian, 23.3% (7) as Hispanic-American, and 13.3% (4) as Asian-American, and 10% (3) identified as other. Participants ranged in age from 19 to 27 years (M = 22.85, SD = 2.42)

Procedure

As part of a larger study, participants completed a baseline assessment and laboratory task session at the George Mason University. At the laboratory task session, participants completed a modified go/no-go task that has orthogonalized action and valence to distinguish Pavlovian bias and instrumental learning, followed by a mood induction, and then a second run of the task. Participants' mood was tracked at several timepoints throughout the session to ensure the mood induction worked. More detailed description of the task session can be found in Study 1.

Following the laboratory task session, participants received training on how to complete the EMA protocol. Participants downloaded an EMA app onto their smartphones and participated in EMA data collection for two weeks. Participants were given feedback regarding their compliance at the end of each week. Participants were paid for each week and received a bonus based on compliance to the protocol. Participants earned a maximum of $75.00 for their participation in the study.

Mood induction

The Mood induction task was a Narrative Mood Induction described in study 1. To summarize, participants were read a narrative that they had written before coming to the laboratory task session about the time that they were the angriest. Narrative mood inductions have consistently demonstrated the ability change an individual's current mood to a targeted mood state in several studies (Bodenhausen et al., 1994; Brinol et al., 2007; Goodwin & Williams, 1982; Jefferies et al., 2008).

Pavlovian Bias Go/No-Go Task

Participants completed a modified Go/No-Go task, which orthogonalized action and valence (outcome) to distinguish Pavlovian bias and instrumental learning. For each trial there were three events: a cue, a symbol to represent when the participant should engage their action choice (Go or NoGo), and an outcome. Participants were told to respond to the target ("Go") or they could withhold a response ("NoGo) and that each cue would lead to a reward, a neutral response, or punishment based on their responses and that they should explore both response options to best learn how to achieve the best outcome from each cue. There were four action-reward combinations: Go-to-Win, Go-To-Avoid, NoGo To-Win, and NoGo-to-Avoid. This yielded 4 distinct trial, two of which considered to be Pavlovian congruent (i.e., Go to Win and No-go to Avoid) and 2 Pavlovian incongruent (Go to Avoid and No-go to Win). Each trial began with the display of a colored shape cue. Next, the participants saw the target indicating they should make a decision about which action to choose. The target disappeared if participants pressed the button to indicate they have selected the "Go" option, or after 1000 ms. Then, the participants received visual feedback indicating reward, neutral response, or punishment (green $ indicated a win, a red $ indicated a loss, or yellow equals sign indicated no reward or punishment). Each trial had an 80% chance of providing the appropriate reward for the displayed cue. In total, participants completed 40 trials of each of the 4 action-reward combinations.

EMA paradigm

All EMA data were collected using the Real-Time Assessment In the Natural Environment (ReTAINE) system (http://retaine.org/). ReTAINE is a web-based, data collection system that allows for the gathering of EMA data via smartphones. Participants completed daily ratings of mood, stress, and impulsive behaviors using their smartphone devices for two weeks. Negative affect was assessed by items generated from the Positive and Negative Affect Scale (PANAS; Watson & Clark, 1984), which was rated by on a Likert scale. Two types of daily self-report methods were used: signal contingent and event-contingent. For signal contingent ratings, participants responded to prompts that occurred at six semi-random times throughout the day, determined by randomly selecting times around anchor points between 8:30 a.m. and 10:00 p.m.

Data Analysis Plan

Task-based Analyses: Pavlovian Bias. Performance on the task was used to determine the amount of change in various indices of Pavlovian bias exhibited after experiencing increased anger. Given the results of study 1, several potential moderators were considered. All moderators were calculated as individual difference scores or change scores (run 1 were subtracted from the result of the measures in run 2).

First, changes scores for each individual trial type (i.e., Go-to-Win, Go-To-Avoid, NoGo To-Win, and NoGo-to-Avoid) were calculated. Changes scores for these variables accounted for the amount of change in the percentage of correct responses from run 1 to run 2. For example, if the change score was positive, the individual performed better on the second run than on the first run. Negative scores indicate a poorer performance and a decrease in the percentage correct of the trials in the second. Given Go-to-Win and NoGo-to-Avoid are Pavlovian congruent, while Go-To-Avoid and NoGo To-Win are Pavlovian incongruent, it is possible that change in congruent trials or incongruent trials may differentially impact the trajectory of negative affect to an impulsive behavior

Second, change scores of both reward- invigoration scores [(“Go” responses on Go-to-Win + NoGo-to-Win)/ Total Go conditions] and punishment-based suppression scores [(NoGo on Go-to-Avoid + NoGo-to-Avoid)/Total NoGo] were used as moderators. These scores are derived from the percent correct scores of each of the trials. Change in either of these scores represents a change the likelihood of responding go to reward cue (reward-invigoration) or responding no-go to a punishment cue (punishment suppression). Negative scores indicate a decreased likelihood, while positive scores indicate that individuals are more likely to go for rewards or no-go for punishments.

Third, a Pavlovian bias score was calculated from the reward-based invigoration and punishment-based suppression indices. The Pavlovian bias score incorporates both reward invigoration and punishment suppression. Specifically, the Pavlovian bias score indicates how likely a participant is to respond go to reward cues and respond no-go to punishment cues.

Lastly, several of the computational model parameters were considered as potential moderators. These parameters included: the positive and negative learning rate, reward bias, a go bias, and a Pavlovian bias parameter. Change in the positive and negative learning rates indicates the change in the likelihood an individual can learn the instrumental contingencies of the task. Positive change scores indicate that individuals are more likely to learn while negative scores represent a decreased ability to engage in the instrumental learning of the task. Change in the reward sensitivity index indicates a change in how much an individual weighs getting a reward or punishment when making their decisions. Positive change scores represent an increased reward sensitivity, while negative change scores represent a decreased reward sensitivity. The Go bias parameter accounts for the prepotent tendency for most people to respond go, regardless of the cue. Change in the Go bias parameter from Run 1 to Run 2 represents a change in the likelihood that an individual will respond go, regardless of the cue. Positive Go Bias change scores indicate that an individual is more likely to respond go for any trial, while negative change scores represent a decrease in the likelihood of responding go. Finally, the Pavlovian bias indicates the amount that Pavlovian bias impacts an individual's ability to perform on the task. Positive change scores indicate that Pavlovian bias had more of an impact on performance following the mood induction, while negative scores indicate it had less of an impact following the mood induction.

EMA Analyses. Generalized estimating equations (GEE) were used to examine the temporal relationship between momentary changes in affect and impulsive behaviors. These analyses included the pre- and post-event trajectories of negative affect using piecewise linear, quadratic, and cubic functions centered on the time at which the binge occurred. Models were based upon a gamma distribution with a log link function and a second-order dependent covariance structure to account for correlation across repeated observations. Multilevel models included linear functions (i.e., hours prior to event, hours following event), which reflects the rate of change in affect prior to and following impulsive behaviors, quadratic functions (i.e., [hours prior to event] 2, [hours following event] 2), which reflect the acceleration in rate of affective change prior to and following impulsive behaviors; and cubic functions (i.e., [hours prior to event] 3, [hours following event] 3), which reflect either further acceleration or dampening of the acceleration in rate of affective change. Impulsive behaviors and negative affect data were obtained from responses to signal contingent prompts (occurring at six different times per day), and event contingent data was used as a validity check of the signal contingent data. If more than one impulsive behavior is reported in a single day, only the first behavior was used to avoid confounding the relationship between antecedent and consequent ratings negative affect in relation to the multiple impulsive behaviors throughout any one day. Additionally, if subsequent impulsive behaviors occurred within the 4-hr time frame following the first behavior, only negative affect ratings made after the first behavior and prior to the subsequent behavior were included in the post-event analyses.

Combined EMA and Task analyses. To examine the potential moderating effect of both Pavlovian Performance Bias on the relations between negative affect and impulsive behaviors, difference scores were created by subtracting scores from each domain in Run 2 from Run 1. These variables were used as a moderator of the within day relationship between negative affect and impulsive behaviors in two separate models. Moderation of the model was tested by including these difference score (for both Pavlovian Performance Bias and other indices) as both a main effect and as interactions with each of the time components in the model. All moderators were standardized and mean-centered prior to analyses.

Results

EMA Measurement and Main Effects

Participants provided 2,093 EMA recordings representing 436 separate participant days, an average of 14.5 days per participant. The average compliance rate was 84%. Impulsive behavior episodes were reported on 91 days by 26 participants, with an average of 3.5 episodes per participant. The number of impulsive behaviors over the two weeks ranged from 0-10.

Consistent with previous studies which examined only one behavior considered to be impulsive (i.e., binge eating and substance use), NA significantly increased prior to impulsive behavior and decreased following impulsive behavior. Specifically, the linear ($B = 0.22$, $p < 0.000$), quadratic ($B = 0.03$, $p < 0.000$), and cubic ($B = 0.002$, $p < 0.000$) trajectories all increased prior to the impulsive behaviors. Following the impulsive behavior, the linear ($B = -0.428$, $p < 0.000$) and cubic ($B = -0.003$, $p < 0.000$) trajectories of NA significantly decreased (see Table 2. and Figure 3.).

*Table 2***.** General Estimating Equation Analysis of the Relation Between Negative Affect and Impulsive Behaviors.

Effect	Estimate	SE	p
Intercept	2.592	0.0597	0.000
Hours	0.220	0.0420	0.000
Hours2	0.034	0.0091	0.000
Hours3	0.002	0.0005	0.001
Hours x NA	-0.428	0.0744	0.000
Hours2 x NA	-0.002	0.0109	0.881
Hours3 x NA	-0.003	0.0007	0.000

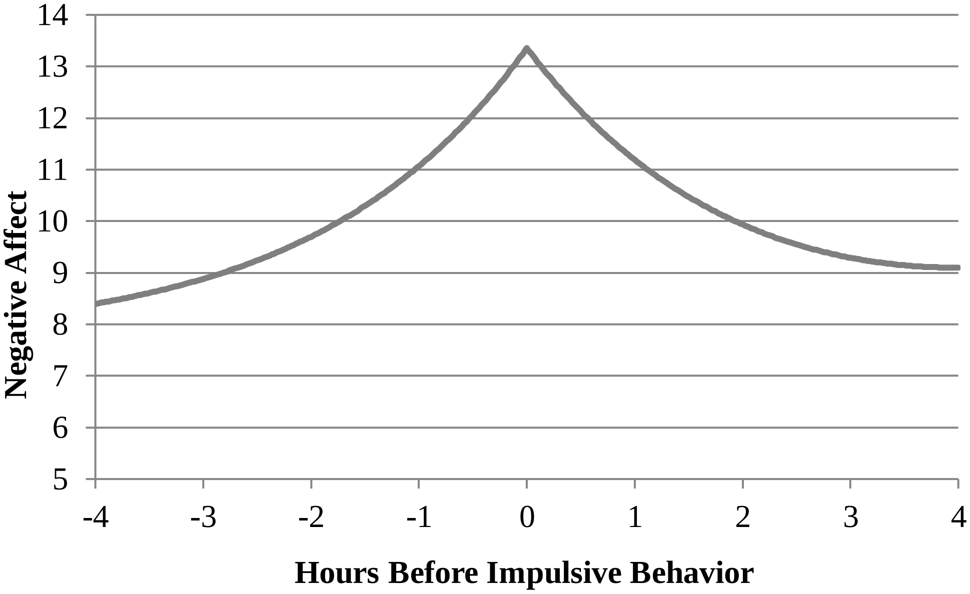

Figure 3. Graph modeling the trajectory of negative affect prior to and following impulsive behavior. ‘0’ represents the point at which an impulsive behavior occurred.

EMA and Task Results

Mood Induction. As previously reported in Study 1, paired samples t-test of the data from the affect grid before and after the anger mood induction revealed a significant increase in arousal from time 1 (M = 4.83, SD = 1.659) to time 2 (M = 5.89, SD = 2.007) (t (29)= 2.62, p = 0.013). Additionally, there was a significant decrease in valence from time 1 (M = 5.91, SD = 1.772) to time 2 (M = 3.66, SD = 1.522) (t (29) = -6.26, p < 0.000).

Moderation of Negative Affect Trajectories. While change in global Pavlovian Performance Bias scores did not significantly moderate the momentary relation between NA and impulsive behaviors, individual differences in the change of two components of Pavlovian bias did significantly moderate this relationship. First, changes in reward-based invigoration scores following an anger mood induction significantly moderated the linear trajectories before (B = -0.093, p = 0.49) and after (B = .137, p = 0.48) an impulsive behavior (see Table 3.). Specifically, individual with a greater decrease in reward-based invigoration scores required less of an increase in NA to engage in an impulsive behavior and experienced less of a less of a decrease following the impulsive behavior (see Figure 4.). Second, the change in the percent correct on Go to Avoid trials (approach-based Pavlovian incongruent trials) following the anger mood induction moderated the linear antecedent trajectory of NA before an impulsive behavior (B = -0.119, p = 0.42;). Following the impulsive behavior, the change in the percent correct on Go to Avoid trials moderated the linear (B = 0.272, p < 0.00) and cubic (B = 0.002, p = 0.02) trajectories of NA (see Table 3.). For individuals with a greater decrease in the percent correct of Go to Avoid trials, there was significantly less of an increase in NA prior to an impulsive behavior and significantly less of a decrease of NA following the behavior (see Figure 5.).

Table 3. General Estimating Equation Analysis for the Moderating Effects of Components of Pavlovian Bias on the Relationship Between NA and Impulsive Behaviors.

	Reward Invigoration Score			**Go to Avoid Performance**		
Effect	**Estimate**	**SE**	**p**	**Estimate**	**SE**	**p**
Intercept	2.559	0.0703	0.000	2.574	0.0561	0.000
Activation	0.233	0.0462	0.000	0.242	0.0436	0.000
Hours	0.037	0.0102	0.000	0.037	0.0101	0.000
Hours2	0.002	0.0006	0.002	0.002	0.0006	0.005
Hours3	-0.453	0.0826	0.000	-0.465	0.0572	0.000
Hours x Moderator	-0.004	0.0097	0.718	-0.003	0.0136	0.803
Hours2 x Moderator	-0.003	0.0009	0.000	-0.003	0.0008	0.000
Hours3 x Moderator	-0.043	0.0951	0.655	-0.322	0.0772	0.000
Hours x NA	-0.093	0.0528	0.049	-0.119	0.0630	0.043
Hours2 x NA	-0.018	0.0108	0.103	-0.017	0.0128	0.174
Hours3 x NA	-0.001	0.0006	0.147	-0.001	0.0008	0.318
Hours x NA x Moderator	0.137	0.0802	0.048	0.272	0.0625	0.000
Hours2 x NA x Moderator	0.016	0.013	0.230	-0.006	0.0197	0.753
Hours3 x NA x Moderator	0.001	0.0008	0.283	0.002	0.0008	0.020

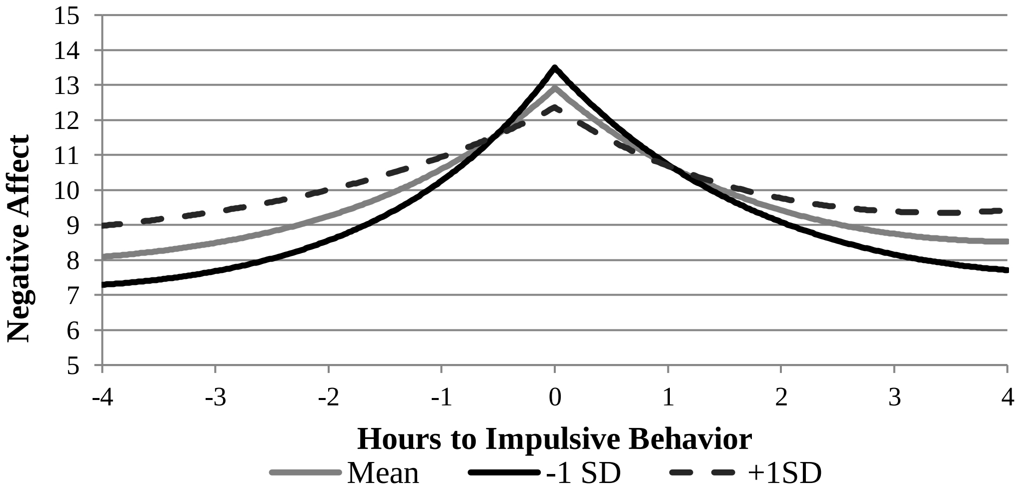

Figure 4. Graph modeling the trajectory of negative affect prior to and following an impulsive behavior as moderated by individual change scores of reward-based invigoration scores following an anger mood induction. Greatest decreases in reward-invigoration are modeled as one standard deviation above the mean decrease. ‘0’ represents the point at which an impulsive behavior occurred.

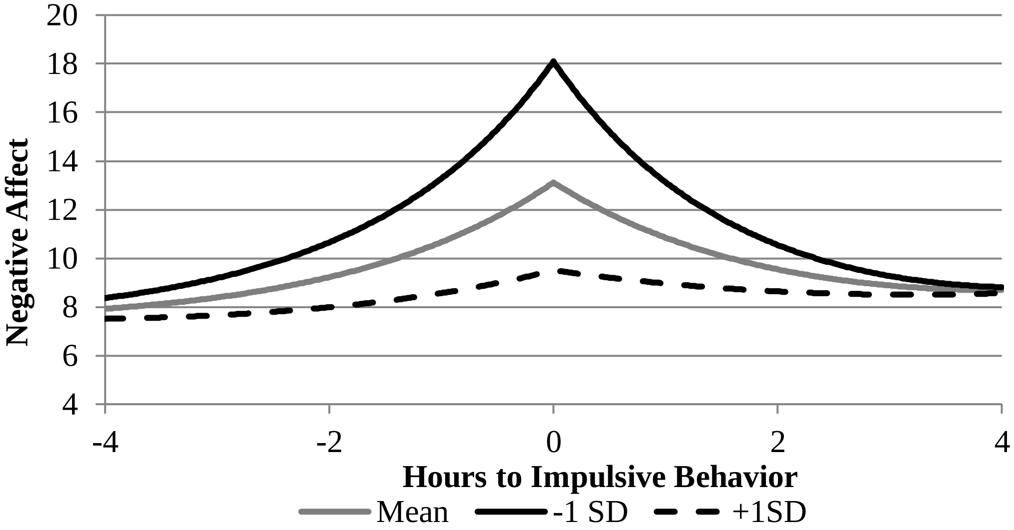

Figure 5. Graph modeling the trajectory of negative affect prior to and following an impulsive behavior as moderated by individual change scores on Go to Avoid (Pavlovian incongruent) trial. Greatest decreases in incongruent performance are modeled as one standard deviation above the mean decrease. ‘0’ represents the point at which an impulsive behavior occurred.

Change in Individual model fit parameters from the computational modeling in study 1, punishment-based suppression scores, or any of the other trials of the task did not significantly moderate the trajectory of NA before or after an impulsive behavior. Lastly, given little variation in the reporting of anger in the EMA, there was no significant change in anger before or after an impulsive behavior. Additionally, none of the variables moderated impacted the momentary relation between anger and impulsive behaviors.

Discussion

Researchers of goal-oriented behavior have previously established that Pavlovian bias impacts decision making by coupling reward seeking with action invigoration and punishment avoidance with action suppression. Additionally, they suggest that Pavlovian bias may be a key factor in understanding why individuals engage in behaviors not in line with their goals. Cavanagh and colleagues (2013) suggest that increased Pavlovian bias is a function of diminished cognitive control abilities, ultimately suggesting that decision making as a product of a Pavlovian bias is impulsive. However, given that several facets of impulsivity imply momentary features, like changes in mood, it is unclear whether or not Pavlovian bias is influenced by acute changes in affect. Additionally, it is unclear whether or not a task of Pavlovian bias, or any of the statistical indices used to analyze the task actually indicate how performance on this task may impact behaviors in the real world. Thus, the goal of this study was to examine how changes in various components of Pavlovian bias as a result of an anger mood induction impact the momentary relation between NA and impulsive behaviors.

While no studies to date have examine the relation of negative affect and a composite score of impulsive behaviors, this study replicated ecologically sensitive results demonstrated in several other impulsive behaviors. Similar to both binge eating and alcohol consumption, the results showed a pattern of increased NA before an impulsive behavior, and decreased NA following the impulsive behavior. Secondly, individual differences in two important components of Pavlovian bias from pre- to post-anger mood induction moderated the trajectory of NA before and after impulsive behaviors.

The results of this study provide some clarity for how Pavlovian Bias laboratory task performance impacts behavior in the real world. The results that suggest that individual differences in reward-based invigorated action and performance on tasks incongruent to Pavlovian bias may influence maladaptive behavioral choices in the face of negative affect. While not all indices of Pavlovian bias moderated the relation between NA and impulsive behaviors, change in both reward invigoration and change in performance on Pavlovian incongruent “Go” trials did moderate this relation. Specifically, people who were more likely approach during the angry mood during the laboratory task were also more likely to engage in what we consider approach related behaviors in real life when they were experiencing negative affect. These findings ultimately suggest that a Pavlovian bias of approaching reward may inform our understanding of impulsive behaviors more than how likely an individual is to avoid punishments.

Other studies utilizing EMA to better understand the relation between NA and impulsive behaviors have found a similar pattern of results when using baseline impulsivity to moderate this relation. For example, Fischer, Wonderlich, Breithaupt, Byrne, & Engel (2018) found that individuals who were more impulsive experienced less of an increase in negative affect to engage in binge eating (an impulsive, maladaptive coping behavior). Additionally, Culbert, Racine, & Klump (2015) found that for individuals who were more impulsive, they experienced a smaller degree of change in negative affect prior to binge eating or purging. These results taken together suggest that perhaps individuals who are more impulsive have a lower threshold for negative affect, and thus, less of increase in negative affect is required to push them to engage in maladaptive, impulsive behaviors which they have learned will alleviate heighted negative affect. It is possible that a similar effect may be present for those who are more suspectable to a Pavlovian bias to approach rewards. Given that individuals who experiences a greater change in reward sensitivity and approach bias also required less of an increase in negative affect to engage in impulsive behaviors, those with a greater bias to approach rewards may also have a lower threshold of tolerating NA, and thus require less of a change in negative affect to engage in impulsive, maladaptive coping strategies

Additionally, results from the integration of EMA and the laboratory task demonstrate the importance of individual differences in relation to behavior outside of the laboratory. While there was no significant group level difference in the Reward-based Invigoration score (see study 1.) from pre- to post-mood induction, individual variation in the change of this metric of Pavlovian bias significantly moderated the trajectory of NA to impulsive behaviors. Specifically, individuals with greater decrease in reward invigoration experience less of an increase in NA before an impulsive behavior compared to those who experiences a less of change in reward invigoration. Greater decreases in reward invigoration were also associated with less of decrease of NA following the impulsive behavior. Furthermore, individual differences in approach-based Pavlovian incongruent trials (Got to Avoid) also moderated the trajectory of NA before and after an impulsive behavior in a similar pattern. Individual with a greater decrease in the percent correct on Pavlovian incongruent trials experienced less of an increase in negative affect compared to those with less of a change in task performance. Thus, there appears to be important individual differences in one’s ability to make goal-oriented decisions while experiencing acute changes in mood.

While other components of Pavlovian bias did not significantly moderate the relation between NA and impulsive behavior, it is unclear whether this is a result of how these variables are calculated or if the variable simply did not impact the relation between NA and impulse behavior. The Pavlovian bias scored used in these tasks is composite of both reward invigoration and punishment suppression. In our data, it appears that as while incongruent trial performance decreased following the mood induction, there was an equivalent increase in congruent trials, ultimately cancelling out the change in which would be observed in the change score of the overall Pavlovian bias score. While overall Pavlovian bias is important in understand group level variables, it appears that reward-invigoration and performance on approach-based incongruent trials may be more ecologically valid metrics to understand how this relation exists in the real world outside of the laboratory.

While this study yields important and novel findings in regard to how changes in mood may impact decision making, limitations of the current study should be noted. First, given the limited reporting of anger during the EMA period, we were not able to examine the relation between anger and impulsive behavior, or how any of the components of Pavlovian bias impact that relation. Given that anger was the emotion used in the mood induction because it was negatively valenced, high arousal, and an approach-based emotion, it is possible that there could be unique relation between these variables aside from those found when using a composite score of negative affect. Second, while the pattern of findings is similar to other studies using clinical samples, this study utilized a college student sample, and thus it’s unclear if these findings would translate. Future research should attempt to replicate these finding using clinical samples of individuals who tend to act more impulsively (e.g., individuals with Binge Eating Disorders, Substance Use Disorders, Borderline personality, etc.) Third, most of the participants were young Caucasian women, thus, our results may not generalize across ethnic groups, gender, or age. Future research might profitably evaluate differential effects across these and other variables. And finally, there was a relatively low distribution across two of the domains used to create the composite score (e.g., binge eating and aggressive behaviors). Future research in this area may want to extend the period of time the participants are enrolled in the EMA protocol in attempts to capture more behaviors.

Despite these limitations, this is the first study to integration trajectory models using EMA data and any laboratory task, and the findings provide promising insight in to better understand impulsive decision making. Additionally, these findings may provide insight into the development of targeted interventions focused on addressing psychopathology with a share mechanism of impulsivity.

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BIOGRAPHY

Joseph A. Wonderlich graduated from Fargo North High School, Fargo, North Dakota, in 2006. He received his Bachelor of Arts from Saint John’s University in Collegeville, Minnesota. He received his Master of Arts in Psychology from George Mason University in 2016.