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Reward-related Predictors of Relapse in Smokers

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REWARD-RELATED PREDICTORS OF RELAPSE IN SMOKERS

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Abstract

Quitting smoking remains an on-going challenging for many cigarette smokers. Numerous individualized characteristics have been suggested as predictors for successful smoking abstinence. One such factor requiring further investigation is reward responsivity, given that individuals with addiction show behavioral and neurobiological alterations in reward function. This study used previously collected data from 122 daily smokers to investigate whether individuals willing to abstain from smoking in exchange for money would display increased reward responsivity during a baseline, non-abstinent visit, relative to individuals who smoked immediately. Participants Probabilistic Reward Task (PRT) performance was used to measure reward responsivity to monetary rewards and a laboratory-based measures of abstinence called the Relapse Analogue Task (RAT) was used to evaluate whether individuals are willing to abstain from smoking in exchange for money. The PRT was analyzed using both traditional analyses and a more fine-grained computational model: Hierarchical Drift Diffusion Modeling (HDDM). Participants fell into 2 groups based on a bimodal distribution of smoking immediately (0-minute waiters) or abstaining the full duration of the RAT (50-minute waiters) and were compared on standard and HDDM PRT measures of reward responsivity. Results showed that 0-minute and 50-minute waiters did not differ on standard nor HDDM measures of reward responsivity, however, 50-minute waiters showed higher values than 0-minute waiters for both standard and HDDM measures of perceptual processing, which were used as control variables. These results suggest individuals who are more likely to abstain from smoking have better perceptual processing abilities, which may be linked to underlying dopaminergic function.

Introduction

Smoking continues to be the leading cause of preventable death in the United States (US Department of Health and Human Services, 2014; USDHHS). It is estimated that 480,000 U.S. deaths per year are caused by cigarette smoking and second-hand smoke exposure (USDHHS), and deaths from smoking-related diseases are proportionally highest in Europe and the Americas (Goodchild, Nargis, & d'Espaignet, 2018). The annual smoking-related death rate is predicted to increase to 8 million people by the year 2030 (World Health Organization, 2011). However, approximately 15.5% of adults in the United States continue to smoke despite the negative health consequences (CDC, 2018). In fact, more than 16 million Americans live with a smoking-related disease, including cancer, heart disease, chronic obstructive pulmonary disease, rheumatoid arthritis, and diabetes. In addition to smoking's overall impact on health, it also has a profound economic cost. For instance, in 2012 the total global economic cost of smoking was $1.4 trillion (Goodchild, Nargis, & d'Espaignet, 2018).

Unfortunately, even for those individuals who try to quit, the rates for successful abstinence remains low. It is estimated that 95% of individuals who attempt to quit without formal treatment relapse within 1 year (CDC, 2011), and, of those who participate in smoking-cessation treatments, only 10-40% remain abstinent (USDHHS, 2008). In fact, many smokers make several attempts to quit (Stapleton, 1998), upwards of 14 attempts before achieving long term abstinence (Chaiton et al., 2016). Thus, it is critical that resources be put into understanding and developing effective smoking-cessation treatments, especially given that health risks associated with smoking can be reversed (USDHH, 1990) and years of life lost from smoking can be reduced by 90% if cessation is achieved by the age of 40 (USDHH, 2014).

Factors Predicting Successful Quitting

When it comes to smoking cessation, there is a broad continuum of how difficult successfully quitting can be. For instance, some people are able to quit without intervention on their first attempt, while others require multiple attempts or are unable to quit all together. Thus, identifying individuals who will or will not find quitting an easy process is an important goal because it will ultimately inform what cessation strategy will be most effective and facilitate individualized treatment plans (Caponnetto & Palosa, 2008). While relapse prevention research has begun to explore some of the mechanisms and factors that contribute to the success of quit attempts, there is much that is not understood. One promising area of research is examining factors that can predict the success of abstinence. Specifically, baseline factors including demographic, health-related, psychological, and smoking-related factors, have all been linked to successful quit attempts.

Demographic variables, such as gender, age, marital status, and years of education, are some examples of specific factors linked with smoking cessation. For instance, women attempt to quit smoking at about the same rate as men but are less likely to succeed (Scharf et al., 2004; Swan et al., 1997; USDHHS, 2001). Age is also linked to successful quit attempts, such that higher success rates are typically reported for older subjects (Hymowitz et al., 1997; Lee et al., 2007; Monso et al., 2001). Another such factor is marital status, with being married a strong predictor of success (Monso et al., 2001). More specifically, smokers are more likely to remain abstinent if they are married to non-smokers or ex-smokers (McBride et al., 1998). Similarly, other family members' smoking status is also predictive of achieving abstinence, such that the absence of other smokers in the household is a strong predictor of success (Gourlay et al., 1994). Finally, there is some evidence suggesting that education level is predictive of smoking

cessation; however, this evidence is mixed. While some studies show that smoking cessation is more likely with higher education (Janson et al., 2006), others suggest that an education level below high school is predictive of successful cessation (Rafful et al., 2013).

In addition to demographic variables, psychological factors also contribute to maintaining abstinence. Individual variability in self-control resources is an important factor in quitting smoking. Specifically, theories of self-control assert that it is a limited resource that can be depleted overtime (Baumeister et al., 1998). Depletion of self-control is linked with nicotine craving, such that, after periods of utilizing self-control resources, smokers deprived of nicotine had an increased craving to smoke (Heckman et al., 2017). Similarly, impulsivity is a key variable when considering an individual's likelihood for successful quitting. One study found that higher levels of self-reported trait-impulsivity predicted quicker relapse after a 48-hour period of abstinence (Doran et al., 2004), and, in another study, tobacco smokers who did not achieve abstinence were more impulsive at the beginning of treatment and had a tendency to discount monetary rewards more than those who remained abstinent (Krishnan-Sarin et al., 2007). Other psychological factors include self-efficacy and negative emotionality. Smokers who remained abstinence for a 6-week period reported higher levels of self-efficacy at baseline (Smit et al., 2014), and individuals with higher negative emotionality were less likely to initiate quitting and were quicker to relapse (Leventhal et al., 2012).

Smoking-related variables are also key factors that are predictive of a successful quit attempt. Smokers' craving intensity during the first few days of a quit attempt predicts future success at quitting (Ferguson et al., 2006). Individuals' attentional bias towards smoking-related stimuli also predicts success; specifically, individuals showing more attentional bias to smoking-related words on the first day of a quit attempt were more likely to relapse (Waters et al., 2003).

Finally, age at smoking initiation is also linked to successful quit attempts, as those who start smoking before 16 are more likely to relapse than those who start at a later age (Breslau & Peterson, 1996). Similarly, initiation of smoking after age 20 is a significant predictor of smoking cessation (Hymowitz et al., 1997).

Nicotine's Effect on Reward Function

Individuals' ability to change behavior based on the past consequences of their behavior is fundamental to successful daily, goal-directed actions. One example is reward responsivity, which describes how individuals modify their behavior based on previous positive reinforcement (Pizzagalli, Jahn & O'Shea, 2005). This reward response can be captured through behavior (Pizzagalli, Jahn & O'Shea, 2005; Pizzagalli et al., 2008; Barr et al., 2008) and even neurobiological responses (see Wang, Smith, & Delgado, 2016, for review). The concept of reward responsivity is rooted in both classical and operant conditioning theories, which explain how conditioned stimuli acquire the ability to elicit behavioral responses through their associated rewarded outcomes. In the context of nicotine addiction, both classical and operant learning are at play; the pleasurable effects of nicotine become classically conditioned to smoking-related stimuli (e.g., cigarettes, ashtrays, smell of tobacco) and, through operant learning, these stimuli develop the ability to trigger habitual smoking behavior (see Belin et al., 2009 for review; Field & Cox, 2008).

Some of the brain regions underlying classical and operant learning processes are located in the striatum (e.g., nucleus accumbens; Hall et al., 2001; Parkinson et al., 2002), which serves a significant role in processing rewards and integrating information about rewards into future behavior (Tricomi et al., 2004; O'Doherty et al., 2004). In order for stimuli to acquire the ability to trigger behaviors, they must first be encoded as resulting in rewards, which is facilitated by

dopamine release in reward-related brain regions (i.e., striatum; Di Chiara, 1995; Schultz, 2002; Smith-Roe & Kelley, 2000). One of the reasons for the difficulty of successful smoking cessation is nicotine's ability to enhance the brain's reward function by triggering increases in dopamine release (Barrett et al., 2004; Brody et al., 2004). These changes in dopamine levels contribute to short- and long-term neuroadaptations in the reward system (for review, see Adinoff, 2004). Specifically, there is evidence demonstrating that acute nicotine administration in rodents reduces brain reward thresholds, which results in increased reward sensitivity (i.e., a propensity to pursue and experience pleasure from rewards; Bornstein & Marc, 2008; Huston-Lyons & Kornetsky, 1992; Xue et al., 2020). In animal models, increased reward sensitivity (i.e., decreased reward thresholds) can last for up to 36 days after acute nicotine administration (Kenny & Markou, 2006), and, with chronic use, can lead to increases in reward thresholds (i.e., decreased reward sensitivity), especially during periods of withdrawal (Koob & Le Moal, 2001). As a result, it is speculated that individuals continue using nicotine as a way to lower reward thresholds, facilitating their experience of reward (Koob & Le Moal, 2001).

During nicotine abstinence, animal models have been used to show the opposite effect, where reward thresholds are heightened and there is a decrease in reward sensitivity (Epping-Jordan et al., 1998). In fact, even stimuli associated with nicotine-withdrawal develop the ability to elevate reward thresholds on their own, which has been shown in rodent models (Kenny & Markou, 2005). In humans, decreased reward sensitivity, particularly to non-drug rewards, has been demonstrated behaviorally using tasks that give monetary incentives for accurate performance. In these studies, abstinent smokers demonstrate worse performance on reward-responsivity tasks as compared to when they have been administered nicotine (Al-Adawi & Powell, 1997; Pergadia et al., 2014; Powell et al., 2002), to satiated smokers (Powell et al.,

2002), and to non-smokers (Al-Adawi & Powell, 1997; Lesage et al., 2017; Powell et al., 2002; Powell et al., 2004). This reduction in reward-related performance reflects a decreased impact of rewards on the modulation of behavior. Furthermore, these effects can occur as soon as 24 hours after nicotine withdrawal (Pergadia et al., 2014) and can be reversed with nicotine administration (Dawkins et al., 2006). It is reasonable to conclude that such reduced reward responsivity contributes to withdrawal-related symptoms and perpetuates smoking behavior (De Biasi & Dani, 2011).

Theoretical models posit that, during periods of abstinence, drug-related stimuli become more salient and increase in motivational value (Goldstein & Volkow 2002), which increases the probability that individuals will engage in drug-taking behavior. This has been well supported by neuroimaging studies demonstrating that smokers deprived of nicotine are more responsive to smoking-related stimuli, such as images of cigarettes. Specifically, smokers demonstrate increased neural responding to smoking images relative to neutral images during acute nicotine deprivation (David et al., 2005; Due et al., 2002; Falcone et al., 2016; McClernon et al., 2009). Furthermore, these images elicit neural responses in reward-related regions known to respond to addictive drugs, such as nicotine (David et al., 2005; Due et al., 2002; Falcone et al., 2016), which indicates that the reward system is biased towards drug-related stimuli in the environment. Therefore, drug-related stimuli have the ability to trigger similar brain regions as the drug itself.

Thus, while nicotine's initial reinforcing effects come from its ability to increase reward sensitivity, during deprivation there is a hyposensitivity to non-drug rewards and increased responsivity to drug-rewards. This paradoxical relationship is believed to contribute to relapse because abstinent smokers are surrounded by an environment in which typically rewarding stimuli lose their reward-value and drug-related stimuli increase in value (Goldstein & Volkow,

2002). However, it is important to note that investigations on the effects of nicotine on the reward system differ on multiple factors, such as species (e.g., animals vs. humans), pattern of use (e.g., nicotine-naive vs. chronic users), and drug state (e.g., deprived vs. sated). These factors contribute to the variability in findings and warrant further investigation regarding the effect of nicotine on reward sensitivity.

Neural Patterns of Reward Predicting Relapse

One pre-quit factor that requires further investigation is reward processing, given that reward-related deficits are well documented in individuals with substance use disorders. Limited research investigating behavioral manifestations of reward dysfunction as a predictor of relapse currently exists. However, some studies have begun to identify patterns of neural activation in reward-related brain regions associated with successful nicotine abstinence. These studies focus on reward processing *prior* to abstinence (i.e., while satiated) and use brain responsivity to smoking-related and non-smoking related stimuli to predict relapse.

Pre-quit deficits in processing natural rewards, such as pleasant images, are linked with a greater likelihood of relapse during a quit attempt (Versace et al., 2011; Versace et al., 2014). Specifically, smokers with more blunted responsivity to images of pleasant stimuli are less likely to be abstinent after 10 weeks compared to those with a less blunted response (Versace et al., 2011). Similarly, smokers showing lower brain responsivity to pleasant stimuli relative to cigarette-related images prior to quitting are less likely to be abstinent after 6 months (Versace et al., 2014). Furthermore, individual variability in the degree to which smokers process non-drug rewards exists and is shown to predict future smoking behavior (Wilson et al., 2014). Specifically, individuals with weaker neural response to non-drug rewards (e.g., money) are the least willing to refrain from smoking in exchange for money (Wilson et al., 2014). Taken

together, these results suggest that smokers demonstrate a devaluation of natural rewards and a preference for drug-related rewards, and this pattern is predictive of relapse.

Probabilistic Reward Task: Studying Reward in a Laboratory Setting

Given the available evidence demonstrating reward processing patterns of brain activity prior to relapse, it is reasonable to expect behavioral characteristics of reward processing may also predict smoking behavior. One method for measuring behavioral differences in reward function is the Probabilistic Reward Task (PRT), which is a computerized task that assesses an individual's reward responsiveness (Pizzagalli, Jahn, & O'Shea, 2005). In this paradigm, reward responsiveness is defined as an individual's ability to modulate behavior based on prior reinforcements (Pizzagalli, Jahn, & O'Shea, 2005). This is based on the classical behaviorist view that individuals increase behaviors that are positively reinforced with rewards (e.g. Hull, 1943). Reward responsivity on the PRT is characterized by *response bias*, defined as a tendency to report seeing the more frequently rewarded stimulus more often than the less frequently rewarded stimulus (Pizzagalli, Jahn, & O'Shea, 2005).

Following the procedures used by Pizzagalli, Jahn, and O'Shea (2005), individuals taking the PRT are instructed to perform the task with the aim of winning as much money as possible. Individuals are presented with multiple trials of a mouthless cartoon face on a computer screen. After a brief delay, either a short or long mouth is quickly presented on the screen, and participants are asked to identify which mouth was presented by pushing a button. Both mouth types are presented equally across trials; however, only some correct answers end in monetary feedback (e.g., "correct! You won 5 cents"). Correct identification of one mouth is rewarded three times more often than correct identification of the other mouth, resulting in an asymmetrical reinforcement schedule.

Standard PRT analyses yield several performance parameters, such as *response bias* and *response time*. *Response bias* reflects an individual's tendency to categorize the mouth as the type that is most rewarded during previous trials, regardless of which stimulus was actually presented. Therefore, *response bias* captures an individual's ability to integrate reinforcement history into future behavior that either increases or decreases the likelihood of encountering more rewards (Pizzagalli et al., 2009). When interpreting *response bias*, higher values are thought to reflect greater responsivity to monetary rewards, and individuals with a stronger response bias are considered to have more intact reward responsivity.

Standard PRT analyses also consider *reaction time* during PRT performance. Reaction time generally provides insight into cognitive processes, such as attention and response speed, that impact overall behavioral performance (Pizzagalli, Jahn, & O'Shea, 2005). However, there is also a reward-related component to reaction time that has been demonstrated in studies using the PRT (Pizzagalli, Jahn, & O'Shea, 2005; Bogdan & Pizzagalli, 2006). Specifically, stimuli resulting in more frequent rewards typically elicit shorter reaction times than those less rewarded, presumably because more rewarded stimuli have increased saliency. As such, traditional measures of PRT reaction time can be conceptualized as a composite that incorporate elements of both cognitive processing and reward function.

The PRT was originally developed to measure reward responsivity in individuals with depression (Pizzagalli, Jahn, & O'Shea, 2005; Pizzagalli et al., 2009) and has since been validated for use in multiple, independent samples (e.g., Barr et al., 2008; Pergadia et al., 2014; Janes et al., 2015). For example, studies show that individuals with depressive symptoms, such as anhedonia, develop weaker response biases on the PRT than healthy controls and is predictive of anhedonia levels one month later (Pizzagalli, Jahn, & O'Shea, 2005). Furthermore, the PRT

demonstrates sensitivity for detecting aspects of behavioral reward responsivity. For instance, one study showed that, while individuals diagnosed with depression responded to individual rewards, they were unable to integrate this into behavioral changes and develop a reward bias throughout the task (Pizzagalli et al., 2009). The PRT has also been used to study nicotine-related changes in reward responsivity. Research has shown that acute nicotine administration to non-smokers increased response bias towards the more frequently rewarded stimuli on the PRT (Barr et al., 2008). The effects of nicotine abstinence on reward responsivity in smokers are also demonstrated using the PRT, such that there is a reduction in response bias on the PRT after a 24-hour period of abstinence (Pergadia et al., 2014).

These results demonstrate that the PRT is a valid measure of reward responsiveness across different populations (e.g., smokers, non-smokers, depression) and contexts (e.g., on vs. off nicotine). Moreover, the finding that the PRT response bias parameter can predict future levels of anhedonia (Pizzagalli, Jahn, & O'Shea, 2005) highlight its potential utility as a predictive tool. The direct application of the PRT to assess nicotine-related changes in reward responsivity makes it a viable measure of reward sensitivity for the present study.

Alternative Ways to Analyze PRT Data

In addition to standard analyses, there are options available that allow for more fine-grained analyses of the decision-making process to elucidate reward responsivity. One such method is a computational model referred to as the Hierarchical Drift Diffusion Model (HDDM; Wiecki, Sofer, & Frank, 2013), which can be applied to raw PRT data. The HDDM is an extension of the drift diffusion model (DDM;Ratcliff, 1978), which is a well-established model used to study cognitive processes underlying two-choice decisions (Ratcliff & McKoon, 2008). The DDM has been utilized in studies investigating the influence of drugs (Eikemo et al., 2017;

Pedersen et al., 2017) and psychopathology (Banca et al., 2015; Moustafa et al., 2015) on the decision-making process.

The DDM model (Ratcliff & McKoon, 2008) posits that, when presented with two stimuli, the individual has the opportunity to respond "rich" (i.e., respond to more rewarded stimuli) or "lean" (i.e., respond to less rewarded stimuli), creating two decision boundaries (i.e., rich and lean). The separation between boundaries (i.e., two potential responses) is referred to as the *threshold*, whereby, on each successive trial, a drift process begins from a starting point (somewhere between rich and lean boundaries) and accumulates evidence in favor of each boundary as the decision process progresses. The rate at which an individual accumulates evidence in favor of the stimuli shown is referred to as the *drift rate*, and evidence accumulation continues until one of the response thresholds is crossed (i.e., when a decision is made). An individual's starting point during each trial can be equidistant from the boundaries (i.e., two response options) or it can be closer towards one boundary, in which case there is a *starting bias*, or an *a priori* preference towards one response or another. Thus, behavioral biases towards rewarded stimuli can be measured using the DDM parameters of starting point and the efficiency of evidence accumulation is measured through drift rate.

The primary advantage of the DDM over traditional performance analyses is that it breaks down the decision-making process into its component parts (see Ratcliff et al., 2016, for review), which allows for an investigation into the specific aspects of behavioral performance that may be influenced by reward function. Specifically, rather than just looking at overall performance, measures such as drift rate and starting point bias give information about the components making up the decision-making process on each trial. Thus, using a more nuanced

approach to investigating behavioral responsivity to reward will allow us to elucidate the specific component of behavioral performance that is influencing variability in reward responsivity.

Studying Smoking Relapse in the Laboratory

A number of laboratory models exist to investigate aspects of smoking behaviors; however, few focus on relapse behavior. Those that are available fall under the category of smoking-choice paradigms and evaluate an individual's ability to delay smoking in exchange for later rewards. As such, these paradigms have the ability to measure individual variability in delay discounting and the reinforcing value of smoking (McKee, 2009). During these tasks, participants engage in periods of abstinence and are given the option to remain abstinent in exchange for rewards or to engage in smoking, which yields a measure of an individual's ability to delay gratification in the context of nicotine addiction. These laboratory tasks share a similar goal of evaluating the relative value of smoking after periods of abstinence, with a particular focus on factors that lead to lapses after initiating quit attempts. This area is of particular interest, because studies show that smoking behavior early on during a quit attempt is a significant predictor of future smoking behavior (Westman et al., 1997).

While these paradigms evolved from similar goals, they vary in how they are executed, including variables such as abstinence duration required, reward type, task duration, and reward reinforcement schedule. For example, participants might engage in laboratory tasks after periods of abstinence ranging from 3 hours (McKee et al., 2006; Dallery & Raiff, 2007) to 12 hours (Bold et al., 2013) or over multiple time points during lengthier abstinence periods (e.g., 1 week; Sweitzer et al., 2013). While longer periods of pre-task abstinence (e.g., 12 hours) may be more generalizable to real-life quit attempts, it is plausible that this length of time also leads to poorer engagement in tasks due to nicotine deprivation side effects (e.g., poor concentration). Similarly,

tasks themselves vary in duration from 10 minutes (Dallery & Raiff, 2007) to 2 hours (Mueller et al., 2009), which also influences participant retention and effort during task engagement.

Another factor that differs across paradigms is the increments at which abstinent behavior is reinforced; this varies from seconds (Dallery & Raiff, 2007), to minutes (McKee et al., 2006), to days (Juliano et al., 2006), which allows experimenters a more fine-grained investigation into the impact that reward timing has on behavior. Specifically, laboratory tasks that use reinforcement increments across multiple days appear to be most generalizable to real-life quit attempts, given that individuals are more likely to experience non-drug-related rewards on a daily or weekly schedule, as opposed to seconds or minutes. On the other hand, it is more feasible to execute laboratory tasks involving fewer study visits and less burden on nicotine-deprived participants.

Variability across paradigms is also noted in the schedules of reinforcement, where rewards are delivered incrementally (Mueller et al., 2009), constantly (McKee et al., 2006), or decreasingly (Juliano et al., 2006). One of the benefits to using an incremental reinforcement schedule (i.e., increasing rewards over time) is that it increases the likelihood of study participants engaging in abstinence by offering increasing incentives for remaining abstinent over time (Mueller et al., 2009). On the other hand, using a decreasing reinforcement schedule can be beneficial by allowing concurrent investigation of relapse-related factors that are not strictly due to the reinforcing value of money (Mueller et al., 2009), because individuals remaining abstinent in the context of diminishing financial rewards may be utilizing more intrinsic sources of motivation. In contrast, the use of a constant reinforcement schedule eliminates variables related to magnitude of reward, which could affect individuals' decisions to remain abstinent. Specifically, keeping the reward amount constant allows the focus to be on

individual factors, such as reward responsiveness to non-drug rewards and how it fluctuates over time.

Finally, while the majority of tasks implemented financial rewards in exchange for smoking abstinence, one task used smoking rewards, offering participants more cigarettes for longer abstinence periods (Bold et al., 2013). Unfortunately, the use of drug-specific rewards provides information strictly limited to delay discounting and does not yield insight into relative value of different reward types. As such, paradigms using financial rewards are particularly beneficial because they allow for the investigation of individual variability in the relative value of drug versus non-drug rewards, which simulates real-life quit attempts where sources of motivation to abstain come from non-drug rewards (e.g., health improvements, saving money).

One such task successfully implemented in laboratory paradigms is the Relapse Analogue Task (RAT), which was originally developed in response to an FDA mandate requiring a measure for determining if smoking cessation medications work (McKee, 2009). The RAT is a behavioral task that directly pits smoking rewards against non-smoking rewards by creating a condition where abstinent individuals are given the option to engage in smoking or delay smoking in exchange for a small monetary reward (McKee, 2009). Thus, the choice to smoke prior to the end of the task is the analogue of relapse during quit attempts.

During this task, abstinent individuals are given a tray containing their preferred brand of cigarettes, a lighter, and an ashtray. Individuals are instructed that they may begin smoking at any point during the 50-min session but, for every 5 minutes in which they delay smoking, they would earn $0.20. Individual delay periods could last from 0 to 50 minutes, and they could earn up to $2.00. One of the outcome parameters yielded by this task is referred to as *time delay*, which reflects the amount of time an individual can resist smoking (McKee et al., 2006).

The ecological validity of the RAT has been demonstrated by studies investigating risk factors contributing to smoking relapse (Heckman et al., 2017; Kahler et al., 2014; Leventhal et al., 2014; McKee et al., 2006; McKee et al., 2012). Specifically, these studies show that real-world risk factors, such as self-control capacity (Heckman et al., 2017), alcohol use (McKee et al., 2006), and anhedonia (Leventhal et al., 2014), increase the likelihood of choosing to smoke during the RAT. Given that known risk factors for relapse have predicted smoking behavior during the RAT, it is likely that the RAT is also effective at identifying new risk factors, such as behavioral responsivity to rewards.

Behavioral Reward Responsivity as a Predictor of Smoking Behavior

The health risks associated with smoking and the difficulties surrounding quitting smoking are well documented. With the interest of improving success at quitting, research has attempted to identify factors that predict whether an individual will be successful at achieving cessation. While numerous pre-quit characteristics have been proposed, we are still unable to predict with certainty who will be successful at quitting. Given that reward system deficiencies underlie substance use disorders, it is likely that investigating reward processing prior to quit attempts would be useful in predicting smoking cessation success.

There is some evidence suggesting reward processing is a predictor of abstinence, but the evidence has only been observed at the level of brain activity, not overt behavior. The PRT is a valid measure of behavioral reward responsivity in smokers but has yet to be used to predict smoking behavior. Moreover, studies looking at abstinence typically rely on individuals' self-report about their smoking behavior outside of the laboratory, which prevents standardized, objective measurements. The current study directly investigates the link between behavioral reward responsivity and subsequent smoking behavior in a tightly controlled experimental

setting, using a behavioral measure of reward responsivity (i.e., the PRT) followed by a period of relapse (i.e., RAT). Based on findings from previous neuroimaging studies demonstrating that blunted brain reactivity to non-drug rewards is predictive of relapse, it is reasonable to expect this decreased reward sensitivity can be observed behaviorally through PRT performance and is related to an individuals' ability to remain abstinent during the RAT.

Current Study

The current study will use previously collected data to assess whether measures of behavioral reward responsivity are related to individuals' ability to remain abstinent during an objective, laboratory-based measure of relapse. The study will use reward responsivity data collected during participants' baseline visits, where their behavioral response to monetary rewards was assessed using the PRT. We will also use the RAT data collected during an abstinent study visit, where participants' ability to stay abstinent in exchange for money was assessed. Participants will be divided into two groups based on whether they remained abstinent for the full 50-min or did not wait at all (i.e., 0-minutes) during the RAT. Groups will be compared on HDDM and standard parameters of PRT performance completed during a baseline visit.

Hypotheses

Hypothesis 1: Individuals who smoke immediately versus remain abstinent the full time on the RAT will differ on reward-related HDDM measures of the PRT only.

Hypothesis 1A: Individuals who smoke immediately during visit 2's RAT will show less of a starting point bias during visit 1's PRT than those who are abstinent during the RAT.

Hypothesis 1B: Individuals who smoke immediately during visit 2's RAT will not differ in drift rate during visit 1's PRT from those who remain abstinent during the RAT.

Hypothesis 2: Individuals who smoke immediately versus remain abstinent the full time on the RAT will differ on reward-related standard measures of the PRT only.

Hypothesis 2A: Individuals who smoke immediately during visit 2's RAT will show less of a response bias on the PRT during visit 1's PRT than those who are abstinent during the RAT.

Hypothesis 2B: Individuals who smoke immediately during visit 2's RAT will have slower response times to the more frequently rewarded stimulus on the PRT than individuals who remain abstinent during visit 2.

Hypothesis 2C: Individuals who smoke immediately during visit 2's RAT will not differ on discriminability on visit 1's PRT from those who are abstinent on the RAT.

Hypothesis 3: Given the expected increased sensitivity of the HDDM metrics, the effect size of the HDDM results will be larger than the effect size for the traditional metrics.

Methods

Participants

The sample consisted of 122 non-treatment seeking, daily cigarette smokers who were recruited from the community as part of a larger study (Leventhal et al., 2014) on smoking and personality at the University of Southern California (USC). Participants were included if they were 18 years old or older, regular cigarette smokers for 2 or more years, and currently smoking 10 or more cigarettes per day. Exclusion criteria were a current DSM-IV substance dependence other than nicotine, mood disorder, psychotic symptoms or use of psychiatric medications, breath carbon monoxide (CO) levels of <10 ppm at baseline, and recent use of noncigarette nicotine products. All procedures were approved by the USC Institutional Review Board.

Procedures

The following procedures were part of the larger parent study (Leventhal et al.. 2014). All participants attended three study visits: a baseline visit followed by two counterbalanced study visits; one which the participant had been abstinent for at least 16 hours and one non-abstinent visit. The two study visits occurred within 2-14 days of each other. During the baseline visit, participants first completed informed consent followed by a breath alcohol analysis to ensure blood alcohol levels were not above 0. The Structured Clinical Interview for DSM-IV Non-patient Edition (SCID-NP) was administered to assess substance dependence, affective disorders, and psychotic symptoms. Individuals then completed a set of baseline questionnaires which included measures of demographics, smoking and drug/alcohol use, affective symptoms and psychiatric disorders, personality, and anhedonia/happiness.

Smoking and drug/alcohol-use questionnaires included the Michigan Nicotine Reinforcement Questionnaire, Smoking Abstinence Questionnaire, Fagerström Test for Nicotine Dependence (FTND), Smoking Consequences Questionnaire, Smoking History Questionnaire, Alcohol Use Disorders Identification Test, and Drug Use Questionnaire. Measures of psychiatric disorders and affective symptoms include the Adult ADHD Self-report Scale, PTSD Checklist, Inventory to Diagnose Depression Lifetime Version, Restlessness and Agitation Questionnaire, Anxiety Sensitivity Index, Mood and Anxiety Symptom Questionnaire-Short Form, and Center for Epidemiological Studies Depression Scale. Measures of personality variables include the Aggression Questionnaire, Brief Sensation Seeking Scale, and select items from the Urgency-Premeditation-Perseverance-Sensation Seeking-Positive Urgency (UPPS-P) impulsive behavior scale. Measures of anhedonia include the Apathy Evaluation Scale, Fawcett Clark Pleasure Scale, Pleasure and Health Behavior Inventory, Snaith-Hamilton Pleasure Scale, Subjective

Happiness Scale, Satisfaction with Life Scale, Temporal Experience of Pleasure Scale, Tripartite Pleasure Inventory, and Value of Pleasure questionnaire.

Following questionnaires, participants completed the PRT to evaluate reward responsivity (described below). After the task, participants were assigned to either the abstinent or non-abstinent condition for the subsequent study visit and given instructions on smoking based on their condition assignment. For the abstinent session, individuals were told not to smoke after 8pm the night before the visit, and, for the non-abstinent session, individuals were told to smoke as they normally would. Abstinence was verified prior to study visits by assessing breath carbon monoxide (CO) levels; levels of < 10 ppm were considered abstinent.

Abstinent and non-abstinent sessions were identical, except that, during the non-abstinent visit, participants smoked in the lab at the beginning of the study visit and filled out craving and affect measures pre- and post-cigarette to assess the subjective effects of nicotine. These measures included the Tiffany Craving Questionnaire, Positive and Negative Affect Scale, and Cigarette Rating Scale. Both study visits began with an alcohol breath analysis, followed by breath CO readings (for non-abstinence visit, CO was taken after cigarette smoking). Individuals then completed self-report measures on affect, nicotine withdrawal, and craving, which included the Brief Questionnaire on Smoking Urges, Minnesota Nicotine Withdrawal Scale, Wisconsin Smoking Withdrawal Scale, and Profile of Mood States. Participants completed three computerized tasks to asses motivational salience of rewarding, smoking-related, and aversive stimuli: the Modified Stroop Task, a visual probe task, and a pleasantness rating task. Finally, participants completed the relapse analogue task (RAT), during which they had the option to earn money by delaying smoking or to initiate smoking at any point during a 50-minute session (described below). After this task, participants were given instructions for their next study visit,

which would be the condition to which they were not assigned for the second visit (i.e, participants in the non-abstinent condition at the second visit were assigned to the abstinent condition for the third visit). After the third session, participants were debriefed and paid for their participation.

The procedures relevant to the present study are measures of recent nicotine use (i.e. CO readings), demographic and smoking-related questionnaires (i.e. FTND and Smoking History Questionnaire), the RAT, and the PRT.

Behavioral Tasks

Probabilistic Reward Task (PRT)

Participants completed the PRT during their baseline visit to assess their responsivity to monetary rewards. Following procedures outlined in Pizzagalli, Jahn, and O'Shea (2005), participants completed three blocks of 100 trials, lasting approximately 30 minutes with a 30-second break between each block. Each trial began with the presentation of an asterisk for 500ms on the screen, followed by the presentation of a mouthless cartoon face. After a 500ms delay, either a short mouth (11.5 mm) or long mouth (13 mm) was presented on the face for 100ms and participants were asked to identify which type of mouth they saw by pressing a designated key on the keyboard. An asymmetrical reinforcement schedule was used for rewarding responses such that correct identifications of one of the mouths resulted in positive feedback ("Correct!! You win 5 cents"; i.e., rewarded more often) three times more frequently than correct identifications of the other mouth. During each trial, reward feedback was given after 40 correct trials and participants "earned" a total of $6.00 paid at the end of the session.

Relapse Analogue Task

Participants completed the RAT to assess the relative reward value of smoking during their abstinent study visit. Upon beginning the task, participants were given a tray containing 8 cigarettes, a lighter, and an ashtray. Participants were told that they may begin smoking at any point over the next 50 minutes but for every 5 minutes they remained abstinent they would receive $0.20. Thus, participants were eligible to receive a maximum of $2 for remaining abstinent throughout the entire 50-min period. The delay period was operationalized as the number of minutes (0-50 min) the individual remained abstinent. Once participants chose to smoke or 50-minutes was reached, a self-administration period began where they were told they could smoke as much as they wished over the next 60 minutes. Participants were unaware of this self-administration phase until the end of the delay period. This period was meant to capture amount of smoking after a period of abstinence (or no abstinence for those who choose not to wait). During the self-administration period, they were given a box of 8 cigarettes and a $4.00 credit and told that each cigarette they smoke would cost them $0.50, which again provided participants with a reinforcer for not smoking (McKee et al., 2006). Following this period, they were given a rest period where they were allowed to read magazines, but not allowed to smoke. The rest period was included to prevent the influence of the impending opportunity to smoke if they were to end the delay and self-administration period sooner. Participants were informed prior to the RAT that the study visit would end for everyone at 4:00pm, which helped prevent the possibility that individuals might smoke during the RAT to end the visit sooner.

Analyses

Power Analysis

A priori power analyses showed that, when assuming a moderate effect size, the power for the current study is 0.7, which is slightly below the generally accepted target of 0.8.

However, previously published data on standard PRT and HDDM metrics show medium to large effect sizes (Moustafa et al., 2015; Pechtel et al., 2013; Pizzagalli et al., 2008; Pizzagalli et al., 2009; Pizzagalli, Jahn, and O'Shea, 2005; White et al., 2010). Therefore, a moderate effect size was used in an effort to take a relatively conservative approach. Furthermore, to improve power, participants were grouped based on the bimodal distribution of the RAT, which helped eliminate potential noise from those individuals falling in the middle of the distribution. In the absence of a significant result, it is remains possible that there is an effect that may simply be hindered by a small sample size. Furthermore, this modest power level limits the number of covariates that can be used in analyses because any additional covariates lead to a reduction in power. Thus, only exploratory analyses for covariates will be conducted.

PRT Calculations and Quality Assessment

The main variables of interest used from the standard PRT analyses are *response bias* (RB), which captures preferential responding to the more rewarded stimuli (Pizzagalli, Jahn, & O'Shea, 2005), *discriminability* (i.e., ability to differentiate between stimuli*;* Pizzagalli, Jahn, & O'Shea, 2005*)*, and *response time* (RT; ms; i.e., the average amount of time it takes to make a response. Six *a priori* criteria, based on Pizzagalli, Jahn, and O'Shea, (2005) and Lawlor et al. (2019), were used to identify invalid data excluded for further analysis. Trials were classified as outliers if they had RT's less than 150ms or greater than 2500ms, or if the (log transformed) RT exceeded the participant's mean (log transformed) RT by ±3 standard deviations (SD). Participant datasets were excluded if any of the 3 blocks contained: 20+ outliers, fewer than 24 rich or 7 lean rewards, a reward ratio lower than 2.5, and/or lower than 40% correct for rich or lean trials.

Previously published (Macmillan & Creelman, 1991) signal detection analysis were used to calculate the standard PRT metrics. Specifically, response bias and discriminability were calculated as:

Response Bias: $\log b = \frac{1}{2}\log\left(\frac{\text{RICHcorrect}*\text{LEANincorrect}}{\text{RICHincorrect}*\text{LEANcorrect}}\right)$

Discriminability: $\log d = \frac{1}{2}\log\left(\frac{\text{RICHcorrect}*\text{LEANcorrect}}{\text{RICHincorrect}*\text{LEANincorrect}}\right)$

In line with previously published studies that have found main effects of *Block* (Pizzagalli, Jahn, & O'Shea; Bogdan & Pizzagalli, 2006; Pizzagalli et al., 2008) and *Group* x *Block* interactions (Pechtel et al., 2013) for RB and discriminability, both parameters were evaluated using individual blocks (1,2,3) in a 2-way ANOVA.

For RT, previous studies have found significant main effects of *Block* (Pizzagalli, Jahn, O'Shea, 2005), with shorter RTs in blocks 2 and 3, and *Stimulus*-type (Pizzagalli, Jahn, O'Shea, 2005; Pechtel et al., 2003), with rich stimuli resulting in quicker RTs. Therefore, we used a 3-way ANOVA to evaluate average RT across all three blocks, as well as individual block averages for rich and lean stimuli, respectively, to investigate main effects and interaction effects between *Group*, *Block*, and *Stimulus*-type.

Hierarchical Drift Diffusion Modeling (HDDM)

Following the HDDM software and documentation available at http://ski.clps.brown.edu/hddm_docs/index.html, the HDDM was fit to participants raw RT and accuracy data. Analyses were computed in Jupyter Notebooks (Kluyver et al., 2016), which yielded the primary parameters of interest: *drift rate (v)* and *starting point (z).* Additional HDDM parameters incorporated into the model include *non-decision time* (*t*; time needed for stimulus perception and response execution) and *threshold* (*a*; decision boundary between two choices). All HDDM parameters were allowed to vary as a function of group when setting up the model.

Consistent with previously published studies using HDDM analyses (e.g., Lawlor et al., 2019), statistical significance will be determined be inspecting each parameters posterior distribution and identifying areas with < 5% overlap in the group distributions.

Group Differences in Standard PRT and HDDM Parameters (Hypotheses 1 and 2)

Groups were determined using the bimodal distribution of the RAT's time delay parameter (i.e., 0-minute waiters vs. 50-minute waiters). To investigate the between-group differences on HDDM measures on the PRT (Hypothesis 1), we compared the degree of overlap in the posterior distributions of each HDDM parameter for the two groups. Statistical significance was indicated by < 5% overlap between the 0-minute waiters and 50-minute waiters' distributions. The posterior distributions of *starting point* and *drift rate* means were examined, respectively, to determine if individuals who smoke immediately during the RAT (0-minute waiters) demonstrate a reduced starting point bias (Hypothesis 1A) and slower drift rates (Hypothesis 1B) on the PRT than those who are abstinent during the RAT (50-minute waiters).

Statistical Package for the Social Sciences (SPSS) was used to perform 3-way analysis of variance (ANOVA) to evaluate the main effects of *Group* (0-min waiters vs. 50-min waiters, *Block* (1, 2, 3), and *Stimulus*-type (rich vs. lean) as well as *Block* x *Group*, *Stimulus* x *Group*, and *Block* x *Group* x *Stimulus* interactions on standard PRT metrics (Hypothesis 2). Specifically, three separate 3-way ANOVAs were conducted using *response bias* (Hypothesis 2A), *response time* (Hypothesis 2B), and *discriminability* (Hypothesis 2C) as dependent variables.

Relationship Between Standard PRT and HDDM Parameters (Hypothesis 3)

To investigate whether HDDM results show larger effect sizes than traditional metrics (Hypothesis 3), effect sizes were measured using Cohen's *d* and compared between parameters. A larger effect size will be considered to demonstrate more sensitivity to detecting group

differences on the PRT in decision making. To determine whether differences in effect sizes are statistically significant, Cohen's *d* scores were transformed to z-scores and values greater than 1.65 (equivalent to $p = 0.05$, one-tailed) were considered to demonstrate a significant difference.

Results

Group Characteristics

After inspecting the distribution of the overall sample's (n=122) RAT *time delay* data, two groups became apparent based on the presence of a bimodal distribution. Specifically, the distribution of scores revealed that 36 individuals waited 0-minutes to smoke during the RAT and 44 individuals abstained the full 50-minutes from smoking.

Statistical analyses on demographic and smoking-related characteristics did not reveal any significant differences between groups (Table 1). Specifically, 0-minute (M = 43.69, SD = 10.59) and 50-minute (M = 40.64, SD = 10.88) waiters did not differ on age ($t(78)= 1.27$, $p = 0.209$), sex (Fisher's exact = 0.228), or education ($x^2 = 4.11$, $p = 0.250$). There were no significant differences between 0-minute (M = 5.83, SD = 1.94) and 50-minute (M = 4.93, SD = 2.33) waiters on FTND ($t(78)= 1.86$, $p = 0.067$), average number of cigarettes per day (0-minute: M = 17.79, SD = 5.44; 50-minute: M = 16.5, SD = 7.52); $t(77) = 0.85$, $p = 0.398$), or number of cigarettes smoked prior to baseline study visit (0-minute: M = 5.28, SD = 4.12; 50-minute: M = 4.32, SD = 3.08; $t(78) = 1.19$, $p = 0.237$). Given that groups did not significantly differ on select demographic or smoking-related variables, no further exploratory analyses using covariates were performed.

Normality of Dependent Variables

Prior to conducting multivariate analyses on the standard PRT variables, we tested for normality of the data using visual inspection of the distribution. Specifically, we examined Q-Q

plots, which revealed that all 3 blocks' response bias, reaction time, and discriminability were normally distributed.

Group Differences in HDDM Parameters of PRT

The HDDM analysis revealed significantly faster drift rates for 50-minute waiters (Figure 2a.; M = 1.21, SD = 0.08) relative to 0-minute waiters (M = 0.79, SD = 0.09; proportion of overlap of posterior distribution: $q < 0.0001$). No significant difference in the starting bias parameter emerged between groups (Figure 2b.; $q = 0.373$).

Group Differences in Standard PRT Measures

A 2-way ANOVA with *Block* (1,2,3), and *Group* (0-min waiters vs. 50-min waiters) did not reveal a significant *Block x Group* interaction ($p = 0.622$) on RB (Table 2.). A main effect of *Block* ($F(2,77) = 6.73$, $p = 0.002$) emerged, where Block 3 (M = 0.23, SD = 0.20) elicited significantly higher RBs than Block 1 (M = 0.14, SD = 0.16; $t(79) = -3.74$, $p < .001$) and Block 2 (M = 0.17, SD = 0.21; $t(79) = -2.69$, $p = .009$). The 2-way ANOVA was repeated while controlling for overall discriminability and showed that the *Block x Group* interaction on RB remained non-significant ($F(2,76) = 0.35$, $p = 0.709$) .

A 3-way ANOVA with *Block* (1,2,3), *Group* (0-min waiters vs. 50-min waiters), and *Stimulus* (rich vs. lean) revealed a *Block x Stimulus* interaction for RT ($F(2,77) = 5.04$, $p = 0.009$). Specifically, the difference in RT for rich and lean stimuli significantly varied across blocks, such that the difference within Block 1 was smaller ($M\Delta = -37.91$; $t(79) = -4.38$, $p < .001$) than in Block 2 ($M\Delta = -69.81$; $t(79) = -6.87$, $p < .001$) and in Block 3 ($M\Delta = -71.51$; $t(79) = -7.12$, $p < .001$). Main effects of *Block* ($F(2,77) = 14.79$, $p < 0.001$) and *Stimulus* ($F(2,77) = 58.96$, $p = 0.000$) were also observed. Specifically, significantly slower reaction times emerged during Block 1 (M = 688.49, SD = 248.77) relative to Block 2 (M = 620.07, SD = 204.08; $t(79) = 5.51$,

$p < .001$) and Block 3 (M = 610.60, SD = 200.47; $t(79) = 4.51$, $p < .001$). Finally, rich stimuli (M = 580.05, SD = 186.56) elicited significantly faster RTs relative to lean stimuli (M = 650.76, SD = 214.88; $t(79) = -7.66$, $p < .001$). There were no interaction or main effects of Group on RT.

A 2-way ANOVA with *Block* (1,2,3) and *Group* (0-min waiters vs. 50-min waiters) did not reveal a significant *Block x Group* interaction on discriminability ($p = 0.878$). A main effect of *Block* emerged ($F(2,77) = 7.69$, $p = 0.001$), where block 1 (M = 0.52, SD = 0.28) elicited significantly lower discriminability values than block 2 (M = 0.60, SD = 0.30; $t(79) = -3.34$, $p = 0.001$) and block 3 (M = 0.62, SD = 0.32; $t(79) = -3.70$, $p < 0.000$). A significant between-group differences was observed on the overall average discriminability ($p = 0.002$). A follow-up independent samples t-test revealed that 0-min waiters and 50-min waiters significantly differed on all three blocks, such that 50-min waiters had greater discriminability than 0-min waiters on block 1 ($t(78) = -2.84$, $p = 0.006$), block 2 ($t(78) = -2.79$, $p = 0.007$, and block 3 ($t(78) = -2.92$, $p = 0.005$).

HDDM Versus Standard PRT Parameters

Cohen's D calculations revealed larger effect sizes for HDDM relative to standard PRT parameters (Table 3). Specifically, perceptual processes captured by HDDM's drift rate parameter showed larger effect sizes ($d = 5.07$) than the standard PRT discriminability parameter ($d = 0.44 – 0.66$, Mean $d = 0.58$). The difference between the z-scores was 4.5, which indicates a significant difference in effect size between the standard and HDDM measures of perceptual processes. Reward responsivity captured by HDDM's starting bias parameter showed a larger effect size ($d = 0.77$) than the standard PRT response bias parameter ($d = 0.02 – 0.23$, Mean $d = 0.11$), however, the difference between the two effect sizes was 0.66, which did not suggest a significant difference.

Discussion

Quitting smoking continues to be a challenge for many individuals, especially in the absence of formal treatment. There is significant variability across individuals for how difficult quitting smoking can be. Research has begun to identify factors that predict the degree of difficulty for individuals prior to quit attempts; however, correctly estimating who is likely to be successful during quit attempts remains difficult.

One potential pre-quit factor that could be fruitful for informing future quit attempts is an individual's reward function; specifically, an individual's degree of responding to non-drug related rewards (i.e., reward responsivity). The notion that reward responsivity to non-drug rewards could predict successful quit attempts stems from neuroimaging literature demonstrating that blunted responsivity of reward-related brain regions to non-drug rewards predicts future abstinence (Versace et al., 2011; Versace et al., 2014). Thus, it is plausible that behavioral manifestations of blunted reward responsivity evident prior to initiating abstinence could predict individuals' ability to refrain from smoking, which could ultimately help inform who may need more clinical support during quit attempts.

The current study sought to explore whether individuals who smoke exhibit deficits in behavioral responsivity to monetary rewards prior to a period of abstinence. Our primary hypothesis was that, on an abstinence-required study visit, smokers who were able to refrain from smoking during the RAT would show more responsivity to financial rewards during a baseline non-abstinent study visit. To investigate our hypothesis, we analyzed previously collected data from participants who were grouped based on whether they waited 0 or 50 minutes to smoke during the RAT. Using two different statistical approaches, we compared these groups' reward responsivity on a computerized PRT during another study visit, during which participants

were non-abstinent, by examining differences in response bias, as well as their perceptual processing abilities (i.e., discriminability) and reaction time.

Group Differences in Perceptual Processing

In contrast to our hypothesis predicting no group differences on perceptual processing, we did find between-group differences in HDDM and standard PRT measures of perceptual processing during the non-abstinent baseline visit. Specifically, individuals who waited the full 50-minutes on the RAT before smoking demonstrated better perceptual processing abilities (i.e., drift rate and discriminability) to PRT stimuli. These findings can be understood through existing literature linking dopamine with perceptual decision making (i.e., using sensory information to guide actions; Beste et al., 2018). Specifically, when making decisions based on incoming sensory information, the dopaminergic system has been implicated to some extent in the evidence accumulation process (Beste et al., 2018) and in facilitating behaviors aimed at attaining rewards (Goto & Grace, 2005; Pessiglione et al., 2006). The role of dopamine in perceptual processing, specifically sensory evidence accumulation, has been investigated through the study of individuals with various psychiatric disorders (e.g., Schizophrenia, Obsessive-compulsive Disorder, ADHD, Depression) typically associated with dysfunction along different dopaminergic pathways (Huang et al., 2015; Moustafa et al., 2015; Fosco et al., 2017; Lawlor et al., 2019). These studies show that, relative to healthy controls, individuals with schizophrenia (Moustafa et al., 2015), depression (Lawlor et al., 2019), attention-deficit hyperactivity disorder (Fosco et al., 2017), and obsessive-compulsive disorder (Banca et al., 2015) all show slowed drift rates, suggesting that dopamine likely plays some role in facilitating efficient visual evidence accumulation.

Similar to these psychiatric disorders, dopaminergic function is also implicated in nicotine-dependence via nicotine's ability to trigger dopamine release in areas of the striatum (Volkow & Morales, 2015). Paradoxically, chronic nicotine use can decrease baseline dopaminergic function (Perez et al., 2012). Given that participants in this study met criteria for nicotine-dependence and regularly smoked for an average for 22 years (SD = 11.32), it is possible that decreased baseline dopaminergic function related to chronic nicotine-use may be impacting perceptual processing abilities on the PRT in some individuals more than others. Furthermore, a recent meta-analysis found a negative relationship between dopaminergic function and reward discounting in individuals with addiction but not in other clinical populations (Castrellon et al., 2019), which provides a possible explanation for behavioral differences observed on the RAT. Specifically, their findings might suggest that individuals who waited 50-minutes to smoke during the RAT may have increased dopaminergic function and are less likely to discount delayed rewards. Likewise, given that optimal dopaminergic function is also linked to more efficient visual evidence accumulation (Beste et al., 2018), it makes sense that individuals who waited 50-minutes to smoke on the RAT also had higher drift rates on the PRT. However, these interpretations remain speculative since the current study did not directly measure dopamine and further investigation into its role in PRT and RAT performance is required.

Absence of Group Difference in Reward Responsivity

Contrary to our primary hypothesis, group differences in reward responsivity during the baseline non-abstinent visit were not observed for neither HDDM parameters nor standard PRT variables. These findings can be interpreted through existing literature demonstrating nicotine's ability to heighten reward sensitivity, which may have occurred in our sample as a result of

recent smoking. Specifically, studies using the PRT show that smokers who recently smoked (~4 hours) and non-smokers do not differ in reward responsivity (Peechatka et al., 2015; Janes et al., 2015). Evidence for nicotine's ability to increase reward responsivity in smokers also comes from studies comparing reward responsivity during abstinent versus non-abstinent states (e.g., Dawkins et al., 2006), where nicotine intake leads to higher responsivity to monetary reward in comparison to an abstinent state (Dawkins et al., 2006). Moreover, enhanced reward responsivity after nicotine administration has even been demonstrated in non-smokers, who show increased response bias on the PRT after nicotine-use (Barr et al., 2008), further demonstrating nicotine's ability to enhance reward responsivity acutely in individuals without chronic use. Taken together, these study results demonstrate nicotine's ability to bolster reward responsivity in routine smokers and non-smokers and remediate abstinence-induced blunting of reward responsivity. In light of these findings, it remains a possibility that our two groups did not show significant differences in reward responsivity, because any differences that might have existed were attenuated by recent smoking. Statistical tests comparing the two groups on number of cigarettes smoked prior to the PRT study visit did not reveal significant group differences in the amount smoked, supporting the possibility that similar nicotine-use may have equated groups on reward responsivity. However, this interpretation is purely speculative and future studies should investigate whether nicotine-use contributed to a lack of group difference in reward responsivity by collecting data on time of last cigarette, measuring nicotine biomarkers (e.g., cotinine), and assessing change in reward responsivity on the PRT during an abstinent visit.

An alternative explanation for the lack of group difference is that these individuals did not, in fact, have inherent differences in reward responsivity, regardless of recent smoking status. In other words, it may be that not all individuals who smoke, by default, have deficits in reward

responsivity. There are various other individual factors that could mediate whether reward responsivity deficits manifest in individuals who smoke, such as depression history (Janes et al., 2015; Pergadia et al., 2014). For example, there is evidence showing that abstinence-induced deficits in reward responsiveness on the PRT are more profound in smokers with versus without a history of depression (Pergadia et al., 2014). These results suggest that reward deficits could be more likely to exist in smokers with a history of depression and that nicotine may be more likely to increase reward responsivity in those with pre-existing reward-system deficits (i.e., depression). As such, it may be that individual factors that mediate smoking-induced reward enhancement, such as depression, may not have been present in our sample. Specifically, a current mood disorder was an exclusion criterion for participants, which means that individuals at extreme ends of reward responsivity (e.g., anhedonia) were not represented in this data set and as a result, group differences were not observed.

Along the same lines, it is possible that group differences in reward responsivity were not evident because reward responsivity on the PRT is unrelated to RAT performance. Specifically, individuals' responsivity to rewards on the PRT may not be associated with their decision to smoke immediately or wait the full 50-minutes. One plausible explanation for a lack of relationship is the different rewards types utilized by the tasks. While the PRT offers non-drug, financial rewards, the RAT pits a smoking-reward against a financial reward, which does not allow us to conclude if individuals are choosing to wait 50-minutes on the RAT because of the *type* of reward (i.e., non-drug versus drug) versus the *timing* of the reward (i.e., immediate versus delayed). To examine this possibility, future studies should adapt the PRT to involve smoking rewards and modify the RAT protocol to offer the choice of a smaller immediate versus larger delayed smoking reward.

Finally, another potential explanation for the lack of a group difference in reward responsivity is that groups differed in their ability to discriminate between stimuli, which could have interfered with participants' ability to form a bias. Our finding of significant group differences in measures of discriminability demonstrates that 0- and 50-minute waiters did, in fact, show differences in their ability to complete the task (i.e., task difficulty). Studies using standard PRT analyses typically use discriminability as a control measure to ensure that significant findings related to primary variables of interest (e.g., response bias) are not due to general perceptual impairments or task difficulty (Pizzagalli, Jahn, & O'Shea, 2005). Our finding that groups were significantly different on the HDDM parameter of drift rate also supports the possibility that a difference in stimulus discrimination might contribute the lack of reward responsivity finding, as drift rate represents the process of accumulating visual evidence about stimuli that is required to discriminate between stimuli effectively. However, it is important to note that if discriminability were to interfere with response bias, it would be most apt to increase response bias because participants are more likely to rely on their bias for dictating their decision on how to respond to indistinguishable stimuli. Follow-up analyses looking at a *Group x Block* interaction on RB, while statistically controlling for discriminability still did not yield a significant finding, further suggesting that this was not the case. On the other hand, due to methodological limitations, we could not control for HDDM drift rate while testing group differences for starting bias, and thus we cannot be entirely certain that task difficulty did not hinder group differences in bias formation.

Absence of Group Differences on Response Time

Contrary to our prediction, we did not find significant group differences in response time for responding to more frequently rewarded stimuli (i.e., rich stimuli). However, we did find

significantly quicker response times for rich stimuli across all participants, which is consistent with previous studies (Pechtel et al., 2013; Pizzagalli, Jahn, & O'Shea, 2005; Pizzagalli et al., 2009) and confirms that the PRT effectively elicited preferential responding towards the more rewarded stimuli. Our lack of finding for group differences in response time to rich stimuli is consistent with some previous work using samples with purported reward-responsivity deficits, which also did not find group differences in response time based on stimulus-type (Pechtel et al., 2013; Pizzagalli, Jahn, & O'Shea, 2005; Pizzagalli et al., 2009). Our finding that both groups showed similar response times for rich stimuli is conceivable in light of finding that both groups developed similar response biases on the PRT. Specifically, it suggests that the rich stimuli was not particularly more enticing for one group, which we would expect to yield quicker responses. Furthermore, similarities in response times to rich stimuli provide evidence that there was not group differences in psychomotor function, which was further verified by examining the posterior probability plots of HDDM's *non-decision time* parameter (i.e., time needed to perceive the stimulus and execute a response; Lawlor et al., 2019). Thus, our null findings for group differences in response times for rich stimuli appear to fit with the null findings for group differences on response bias. Finally, through inspecting the HDDM *non-decision time* distributions, we can also verify that our significant drift rate findings are mainly reflecting differences in evidence accumulation and not simply psychomotor processes.

HDDM Effect Sizes are Larger than Standard PRT Parameters

Consistent with our hypothesis, HDDM parameters (i.e., drift rate) showed significantly larger effect sizes than standard PRT parameters (i.e., discriminability) for perceptual processing abilities. While HDDM measures of perceptual processing on the PRT were superior to standard metrics, we did not find a significant difference in effect sizes for reward sensitivity. The lack of

finding for reward responsivity suggests that either there was truly an absence of group differences for reward responsivity undetectable by any analyses or that HDDM is not necessarily better at detecting reward sensitivity. However, it is more likely that there were not group differences in reward responsivity given the RB findings from the standard PRT analysis. The larger effect size observed for HDDM measures of perceptual processing further corroborates one of HDDM's noted strengths, which is its capability of detecting more nuanced features of behaviors during decision-making tasks.

Conclusions

Quitting smoking continues to be an ongoing challenge for many individuals. Identifying individuals with the most difficulty quitting remains an important research target because it might inform who would benefit most from specific interventions (e.g., behavioral versus pharmacological). While some potential predictive factors have been identified, it remains unclear who will have the most difficulty remaining abstinent during quit attempts.

One potential factor that could be used to predict whether individuals can abstain from smoking is behavioral reward responsivity to non-drug rewards. It is plausible that reward responsivity could hold predictive validity because neuroimaging data looking at brain responsivity to non-drug rewards have found that blunted responsivity to non-drug rewards is predictive of smoking relapse, suggesting that behavioral correlates of reward responsivity may also hold some value in predicting who can remain abstinent.

Contrary to our hypothesis, the current study's findings did not suggest that behavioral responsivity to financial rewards predicts abstinence behavior during a laboratory abstinence task. Instead, our results show that individuals' ability to remain abstinent during the RAT task is predicted by their ability to accumulate visual evidence to discriminate between stimuli on the

PRT. Specifically, individuals with better perceptual discrimination, measured by both standard and HDDM PRT parameters, were more likely to wait the full 50-minutes before smoking during the RAT. We hypothesize that our null results related to reward responsivity reflect nicotine's ability to correct reward deficits given that the current study sample smoked comparably prior to completing the PRT. The finding that individuals who waited 50-minutes were better at discriminating between stimuli suggests that there could be between group differences in perceptual processing abilities that should be the focus of future addiction research.

Additionally, our results suggest that, if one were to use the PRT as a way to predict successful abstinence, careful consideration of methodology for analyzing PRT performance is necessary. Specifically, using HDDM measures of PRT performance may be more effective than standard PRT measures at elucidating nuanced individual differences in perceptual processing abilities. This knowledge is important for future studies that may look into the clinical utility of the PRT, given that selecting a sensitive measure of behavior is pivotal to clarifying the PRT's value in predicting abstinence.

Clinical Implications

The results from the current study demonstrate that individuals who were willing to abstain from smoking in exchange for financial compensation have better perceptual processing abilities than those who were not. These results suggest that there are factors other than reward-related processes contributing to an individual's ability to remain abstinent from smoking in exchange for non-drug rewards.

Moreover, because perceptual processing was measured after recent nicotine intake, we are able to conclude that this characteristic is not entirely remediated by nicotine, making it particularly useful clinically. In fact, it is reasonable to consider that administering the PRT prior

to a quit attempt will identify individuals that will have more difficulty remaining abstinent, ultimately informing the approach taken for treatment. For instance, individuals with better perceptual processing may be more appropriate for treatment interventions involving behavioral contingencies, while those with deficits may benefit more from pharmacotherapy targeting dopaminergic function or using nicotine replacement therapy. While further investigation into the clinical utility of the PRT for predicting quit attempts is needed, these findings are an important first step.

Given that we did not measure reward sensitivity or perceptual processing during abstinence nor did we measure blood-nicotine levels, we cannot determine whether the significant between-group differences in perceptual processing abilities was a result of nicotine's pharmacological effects or a pre-existing trait. While either possibility could be true, it is likely that both interacted to contribute to our findings. Specifically, evidence exists demonstrating that pharmacological modulation of dopamine increases efficiency of the sensory accumulation process (i.e., drift rate), but this effect follows an inverted u-shaped curve, where too much dopamine results in impairment (Beste et al., 2018). Thus, it is plausible that individuals had different baseline levels of dopaminergic function and, as a result, were differentially impacted (i.e., some shifted beyond optimal levels) by nicotine intake on the day the PRT was administered. Importantly, these individual differences in perceptual processing were detectable with nicotine in the system, which makes this particularly useful when considering hypothetical clinical applications. Specifically, this will better allow for identifying individuals who will have difficulty remaining abstinent even before making a quit attempt, which is important for predicting the number of quit attempts necessary before long-term abstinence is achieved. Importantly, before any clinical conclusions can be drawn, these results require numerous

replications across different demographic populations and using various reward responsivity tasks, to verify that there is in fact a relationship between drift rate and abstinence behavior.

Limitations

While the current study provides compelling evidence for perceptual processing differences between two groups of smokers, it is not without limitations. First, the PRT was not administered on the same day as the RAT, which increases the opportunity for extraneous variables between study visits, such as menstrual cycle and life stressors, to potentially influence the results. However, this experimental design also has the most ecological validity for how the PRT may be utilized clinically, where it could be administered under satiety days or weeks in advance of a quit attempt and still hold some predictive ability. Similarly, the PRT was given to participants after recent smoking, which does not allow us to draw conclusions about abstinence-induced deficits in perceptual processing. Given that reward-related deficits often emerge during periods of nicotine-abstinence, recent smoking may have equalized any differences in reward responsivity on the PRT that would have been evident during abstinence. Moreover, measuring PRT performance during periods of abstinence would also improves translation between PRT and RAT behavior, since the RAT was conducted during an abstinent study visit. Finally, individuals included in our sample were not required to be treatment seeking, and, as a result, individuals likely differed in their baseline levels of motivation to quit smoking. For instance, individuals contemplating making a quit attempt may have experienced waiting to smoke during the RAT easier than individuals less interested in quitting. Another important consideration for our study is that we were not able to assess the degree to which people made decisions based on reward preference (i.e., drug versus non-drug) or as a result of delayed discounting tendencies, both of which have been implicated in addiction. Specifically, the 0-minute waiters may have

found the nicotine-reward to be more enticing than a financial reward (i.e., greater valuation of drug reward). Alternatively, it is possible that the delayed nature of the financial reward may have diminished its value, and the option for the immediate reward (i.e., cigarette) may have been more enticing.

Future Directions

Future research replicating the current study should further evaluate the clinical utility of the PRT by increasing the amount of time between PRT and RAT to determine how far in advance PRT performance can predict behavior during the RAT. Likewise, future studies should investigate the impact that biological changes, such as hormones, occurring between visits have on PRT performance and PRT's ability to predict of abstinence behavior. Additionally, this study should certainly be replicated using different payment amounts during the RAT to investigate whether the bi-modal distribution reflects individuals who differ in their preference of drug vs. non-drug reward. To link these behavioral findings with their neurobiological underpinnings, future studies using neuroimaging techniques are necessary for elucidating if reward-related brain regions and metabolic processes related to dopamine are triggered during these tasks. Finally, replication of the current study in a treatment-seeking sample should involve administering the PRT prior to quitting and follow individuals longitudinally during in vivo quit attempts. This replication is necessary for increasing our understanding on the clinical utility of PRT measures for informing individual differences in quitting smoking. Moreover, studying the ability of PRT performance to predict real-world quit attempts would improve ecological validity of our findings.

References

Adinoff, B. (2004). Neurobiologic processes in drug reward and addiction. *Harvard Review of Psychiatry*, *12*(6), 305–320. https://doi.org/10.1080/10673220490910844

Al-Adawi, S., & Powell, J. (1997). The influence of smoking on reward responsiveness and cognitive functions: A natural experiment. *Addiction*, *92*(12), 1773–1782. https://doi.org/10.1111/j.1360-0443.1997.tb02897.x

Banca, P., Vestergaard, M. D., Rankov, V., Baek, K., Mitchell, S., Lapa, T., … Voon, V. (2015). Evidence accumulation in obsessive-compulsive disorder: The role of uncertainty and monetary reward on perceptual decision-making thresholds. *Neuropsychopharmacology*, *40*(5), 1192–1202. https://doi.org/10.1038/npp.2014.303

Barr, R. S., Pizzagalli, D. A., Culhane, M. A., Goff, D. C., & Evins, A. E. (2008). A single dose of nicotine enhances reward responsiveness in nonsmokers: Implications for development of dependence. *Biological Psychiatry*, *63*, 1061–1065. https://doi.org/10.1016/j.biopsych.2007.09.015

Barrett, S. P., Boileau, I., Okker, J., Pihl, R. O., & Dagher, A. (2004). The hedonic response to cigarette smoking is proportional to dopamine release in the human striatum as measured by positron emission tomography and [11C]raclopride. *Synapse*, *54*(2), 65–71. https://doi.org/10.1002/syn.20066

Baumeister, R. F., Bratslavsky, E., Muraven, M., & Tice, D. M. (1998). Ego depletion: Is the active self a limited resource? *Journal of Personality and Social Psychology, 74*, 1252–1265. http://dx.doi.org.ezp-prod1.hul.harvard.edu/10.1037/0022-3514.74.5.1252

Belin, D., Jonkman, S., Dickinson, A., Robbins, T. W., & Everitt, B. J. (2009). Parallel and interactive learning processes within the basal ganglia: Relevance for the understanding of addiction. *Behavioural Brain Research*, *199*(1), 89–102. https://doi.org/10.1016/j.bbr.2008.09.027

Beste, C., Adelhöfer, N., Gohil, K., Passow, S., Roessner, V., & Li, S. (2018). Dopamine Modulates the Efficiency of Sensory Evidence Accumulation During Perceptual Decision Making. *International Journal of Neuropsychopharmacology*, *21*(7), 649–655. https://doi.org/10.1093/ijnp/pyy019

Bogdan, R., & Pizzagalli, D. A. (2006). Acute Stress Reduces Reward Responsiveness: Implications for Depression. *Biological Psychiatry*, *60*(10), 1147–1154. https://doi.org/10.1016/j.biopsych.2006.03.037

Bold, K. W., Yoon, H., Chapman, G. B., & McCarthy, D. E. (2013). Factors predicting smoking in a laboratory-based smoking-choice task. *Experimental and Clinical Psychopharmacology*, *21*(2), 133–143. https://doi.org/10.1037/a0031559

Borrelli, B., Hogan, J. W., Bock, B., Pinto, B., Roberts, M., & Marcus, B. (2002). Predictors of quitting and dropout among women in a clinic-based smoking cessation program. *Psychology of Addictive Behaviors*, *16*(1), 22–27. https://doi.org/10.1037/0893-164X.16.1.22

Bornstein, & Marc. (2018). *The SAGE Encyclopedia of Lifespan Human Development* (1st ed.). US: Sage Publications.

Breslau, N., & Peterson, E. L. (1996). Smoking cessation in young adults: Age at initiation of cigarette smoking and other suspected influences. *American Journal of Public Health, 86*(2), 214-220. https://doi.org/10.2105/AJPH.86.2.214

Brody, A. L., Olmstead, R. E., London, E. D., Farahi, J., Meyer, J. H., Grossman, P., Lee, G. S., Huang, J., Hahn, E. L., & Mandelkern, M. A. (2004). Smoking-induced ventral striatum dopamine release. *American Journal of Psychiatry*, *161*, 1211–1218. https://doi.org/10.1176/appi.ajp.161.7.1211

Caponnetto, P., & Polosa, R. (2008). Common predictors of smoking cessation in clinical practice. *Respiratory Medicine*, *102*(8), 1182–1192. https://doi.org/10.1016/j.rmed.2008.02.017

Castrellon, J. J., Seaman, K. L., Crawford, J. L., Young, J. S., Smith, C. T., Dang, L. C., Hsu, M., Cowan, R. L., Zald, D. H., & Samanez-Larkin, G. R. (2019). Individual differences in dopamine are associated with reward discounting in clinical groups but not in healthy adults. *Journal of Neuroscience*, *39*(2), 321–332. https://doi.org/10.1523/JNEUROSCI.1984-18.2018

Center for Disease Control and Prevention. (2018). Current cigarette smoking among adults – United States, 2016. *Morbidity and Mortality Weekly Report*, *27*(2), 53- 59. http://dx.doi.org/10.15585/mmwr.mm6702a1

Centers for Disease Control and Prevention. (2011). Cigarette smoking—United States, 1965 – 2008. *Morbidity and Mortality Weekly Report, 60*, 109-113. Retrieved from: https://www.cdc.gov/mmwr/preview/mmwrhtml/su6001a24.htm

Chaiton, M., Diemert, L., Cohen, J. E., Bondy, S. J., Selby, P., Philipneri, A., & Schwartz, R. (2016). Estimating the number of quit attempts it takes to quit smoking successfully in a longitudinal cohort of smokers. *BMJ Open*, *6*, e011045. https://doi.org/10.1136/bmjopen-2016-011045

Dalley, J. W., & Roiser, J. P. (2012). Dopamine, serotonin and impulsivity. *Neuroscience*, *215*, 42–58. https://doi.org/10.1016/j.neuroscience.2012.03.065

David, S. P., Munafò, M. R., Johansen-Berg, H., Smith, S. M., Rogers, R. D., Matthews, P. M., & Walton, R. T. (2005). Ventral striatum/nucleus accumbens activation to smoking-related

pictorial cues in smokers and nonsmokers: A functional magnetic resonance imaging study. *Biological Psychiatry*, *58*(6), 488–494. https://doi.org/10.1016/j.biopsych.2005.04.028

Dawkins, L., Powell, J. H., West, R., Powell, J., & Pickering, A. (2006). A double-blind placebo controlled experimental study of nicotine: I - Effects on incentive motivation. *Psychopharmacology*, *189*(3), 355–367. https://doi.org/10.1007/s00213-006-0588-8

De Biasi, M., & Dani, J. A. (2011). Reward, addiction, withdrawal to nicotine. *Annual Review of Neuroscience*, *34*(1), 105–130. https://doi.org/10.1146/annurev-neuro-061010-113734

Di Chiara, G. (1995). The role of dopamine in drug abuse viewed from the perspective of its role in motivation. *Drug and Alcohol Dependence*, *38*(2), 95–137. https://doi.org/10.1016/0376-8716(95)01118-I

Doran, N., Spring, B., McChargue, D., Pergadia, M., & Richmond, M. (2004). Impulsivity and smoking relapse. *Nicotine and Tobacco Research*, *6*(4), 641–647. https://doi.org/10.1080/14622200410001727939

Due, D. L., Huettel, S. A., Hall, W. G., & Rubin, D. C. (2002). Activation in mesolimbic and visuospatial neural circuits elicited by smoking cues: Evidence from functional magnetic resonance imaging. *American Journal of Psychiatry*, *159*(6), 954–960. https://doi.org/10.1176/appi.ajp.159.6.954

Eikemo, M., Biele, G., Willoch, F., Thomsen, L., & Leknes, S. (2017). Opioid modulation of value-based decision-making in healthy humans. *Neuropsychopharmacology*, *42*(9), 1833–1840. https://doi.org/10.1038/npp.2017.58

Epping-Jordan, M. P., Watkins, S. S., Koob, G. F., & Markou, A. (1998). Dramatic decreases in brain reward function during nicotine withdrawal. *Nature*, *393*(6680), 76–79. https://doi.org/10.1038/30001

Falcone, M., Cao, W., Bernardo, L., Tyndale, R. F., Loughead, J., & Lerman, C. (2016). Brain responses to smoking cues differ based on nicotine metabolism rate. *Biological Psychiatry*, *80*(3), 190–197. https://doi.org/10.1016/j.biopsych.2015.11.015

Ferguson, S. G., Shiffman, S., & Gwaltney, C. J. (2006). Does reducing withdrawal severity mediate nicotine patch efficacy? A randomized clinical trial. *Journal of Consulting and Clinical Psychology*, *74*(6), 1153–1161. https://doi.org/10.1037/0022-006X.74.6.1153

Field, M., & Cox, W. M. (2008). Attentional bias in addictive behaviors: A review of its development, causes, and consequences. *Drug and Alcohol Dependence*, *97*(1–2), 1–20. https://doi.org/10.1016/j.drugalcdep.2008.03.030

Fosco, W. D., White, C. N., & Hawk, L. W. (2017). Acute Stimulant Treatment and Reinforcement Increase the Speed of Information Accumulation in Children with ADHD.

Journal of Abnormal Child Psychology, *45*(5), 911–920. https://doi.org/10.1007/s10802-016-0222-0

Goldstein, R. Z., & Volkow, N. D. (2002). Drug addiction and its underlying neurobiological basis: Neuroimaging evidence for the involvement of the frontal cortex. *American Journal of Psychiatry*, *159*(10), 1642–1652. https://doi.org/10.1176/appi.ajp.159.10.1642

Goodchild, M., Nargis, N., & D'Espaignet, E. T. (2018). Global economic cost of smoking-attributable diseases. *Tobacco Control*, *27*(1), 58–64. https://doi.org/10.1136/tobaccocontrol-2016-053305

Goto, Y., & Grace, A. A. (2005). Dopaminergic modulation of limbic and cortical drive of nucleus accumbens in goal-directed behavior. *Nature Neuroscience*, *8*(6), 805–812. https://doi.org/10.1038/nn1471

Gourlay, S. G., Forbes, A., Marriner, T., Pethica, D., & Mcneil, J. J. (1994). Prospective study of factors predicting outcome of transdermal nicotine treatment in smoking cessation. *British Medical Journal*, *309*(6958), 842–846. https://doi.org/10.1136/bmj.309.6958.842

Hall, J., Parkinson, J. A., Connor, T. M., Dickinson, A., & Everitt, B. J. (2001). Involvement of the central nucleus of the amygdala and nucleus accumbens core in mediating pavlovian influences on instrumental behaviour. *European Journal of Neuroscience*, *13*(10), 1984–1992. https://doi.org/10.1046/j.0953-816X.2001.01577.x

Heckman, B. W., MacQueen, D. A., Marquinez, N. S., MacKillop, J., Bickel, W. K., & Brandon, T. H. (2017). Self-control depletion and nicotine deprivation as precipitants of smoking cessation failure: A human laboratory model. *Journal of Consulting and Clinical Psychology*, *85*(4), 381–396. https://doi.org/10.1037/ccp0000197

Huang, Y. T., Georgiev, D., Foltynie, T., Limousin, P., Speekenbrink, M., & Jahanshahi, M. (2015). Different effects of dopaminergic medication on perceptual decision-making in Parkinson's disease as a function of task difficulty and speed-accuracy instructions. *Neuropsychologia*, *75*, 577–587. https://doi.org/10.1016/j.neuropsychologia.2015.07.012

Hull, C.L. (1943). *Principles of behavior. An introduction to behavior theory*. New York: Appleton-Century-Crofts.

Huston-Lyons, D., & Kornetsky, C. (1992). Effects of nicotine on the threshold for rewarding brain stimulation in rats. *Pharmacology, Biochemistry and Behavior*, *41*(4), 755–759. https://doi.org/10.1016/0091-3057(92)90223-3

Hymowitz, N., Cummings, M., Hyland, A., Lynn, W., Pechacek, T., Hartwell, T. (1997). Predictors of smoking cessation in a cohort of adults smokers followed for five years. *Tobacco Control, 6*(suppl 2), S57-S62. https://doi.org/10.1136/tc.6.suppl_2.S57

Hymowitz, N., Sexton, M., Ockene, J., & Grandits, G. (1991). Baseline factors associated with smoking cessation and relapse. *Preventive Medicine, 20*(5), 590-601. https://doi.org/10.1016/0091-7435(91)90057-B

Janes, A. C., Farmer, S., Peechatka, A. L., Frederick, B. D. B., & Lukas, S. E. (2015). Insula-dorsal anterior cingulate cortex coupling is associated with enhanced brain reactivity to smoking cues. *Neuropsychopharmacology*, *40*(7), 1561–1568. https://doi.org/10.1038/npp.2015.9

Janson, C., Künzli, N., de Marco, R., Chinn, S., Jarvis, D., Svanes, C., … Burney, P. (2006). Changes in active and passive smoking in the European Community Respiratory Health Survey. *European Respiratory Journal*, *27*(3), 517–524. https://doi.org/10.1183/09031936.06.00106605

Juliano, L. M., Donny, E. C., Houtsmuller, E. J., & Stitzer, M. L. (2006). Experimental evidence for a causal relationship between smoking lapse and relapse. *Journal of Abnormal Psychology*, *115*(1), 166–173. https://doi.org/10.1037/0021-843X.115.1.166

Kahler, C. W., Metrik, J., Spillane, N. S., Day, A., Leventhal, A. M., McKee, S. A., … Rohsenow, D. J. (2014). Acute effects of low and high dose alcohol on smoking lapse behavior in a laboratory analogue task. *Psychopharmacology*, *231*(24), 4649–4657. https://doi.org/10.1007/s00213-014-3613-3

Kenny, P. J., & Markou, A. (2006). Nicotine self-administration acutely activates brain reward systems and induces a long-lasting increase in reward sensitivity. *Neuropsychopharmacology*, *31*, 1203–1211. https://doi.org/10.1038/sj.npp.1300905

Kenny, P. J., & Markou, A. (2005). Conditioned Nicotine Withdrawal Profoundly Decreases the Activity of Brain Reward Systems. *Journal of Neuroscience*, *25*(26), 6208–6212. https://doi.org/10.1523/JNEUROSCI.4785-04.2005

Kluyver, T., Ragan-kelley, B., Pérez, F., Granger, B., Bussonnier, M., Frederic, J., … Willing, C. (2016). Jupyter Notebooks—a publishing format for reproducible computational workflows. *Positioning and Power in Academic Publishing: Players, Agents and Agendas*. https://doi.org/10.3233/978-1-61499-649-1-87

Koob, G. F., & Le Moal, M. (2001). Drug addiction, dysregulation of reward, and allostasis. *Neuropsychopharmacology*, *24*(2), 97–129. https://doi.org/10.1016/S0893-133X(00)00195-0

Krishnan-Sarin, S., Reynolds, B., Duhig, A. M., Smith, A., Liss, T., McFetridge, A., … Potenza, M. N. (2007). Behavioral impulsivity predicts treatment outcome in a smoking cessation program for adolescent smokers. *Drug and Alcohol Dependence*, *88*, 79–82. https://doi.org/10.1016/j.drugalcdep.2006.09.006

Lawlor, V. M., Webb, C. A., Wiecki, T. V, Frank, M. J., Trivedi, M., Pizzagalli, D. A., & Dillon, D. G. (2019). Dissecting the impact of depression on decision-making. *Psychological Medicine*, 1–10. https://doi.org/10.1017/S0033291719001570

Lee, C. W., & Kahende, J. (2007). Factors associated with successful smoking cessation in the United States, 2000. *American Journal of Public Health, 97*(8), 1503-1509. https://doi.org/10.2105/AJPH.2005.083527

Lesage, E., Aronson, S. E., Sutherland, M. T., Ross, T. J., Salmeron, B. J., & Stein, E. A. (2017). Neural signatures of cognitive flexibility and reward sensitivity following nicotinic receptor stimulation in dependent smokers a randomized trial. *JAMA Psychiatry*, *74*(6), 632–640. https://doi.org/10.1001/jamapsychiatry.2017.0400

Leventhal, A. M., Japuntich, S. J., Piper, M. E., Jorenby, D. E., Schlam, T. R., & Baker, T. B. (2012). Isolating the role of psychological dysfunction in smoking cessation: Relations of personality and psychopathology to attaining cessation milestones. *Psychology of Addictive Behaviors*, *26*(4), 838–849. https://doi.org/10.1037/a0028449

Leventhal, A. M., Trujillo, M., Ameringer, K. J., Tidey, J. W., Sussman, S., & Kahler, C. W. (2014). Anhedonia and the relative reward value of drug and nondrug reinforcers in cigarette smokers. *Journal of Abnormal Psychology*, *123*(2), 375–386. https://doi.org/10.1037/a0036384

Macmillan NA, Creelman CD (1991). Detection Theory: A User's Guide. Cambridge University Press: New York.

McBride, C. M., Curry, S. J., Grothaus, L. C., Nelson, J. C., Lando, H., & Pirie, P. L. (1998). Partner smoking status and pregnant smoker's perceptions of support for and likelihood of smoking cessation. *Health Psychology, 17*(1), 63-69. https://doi.org/10.1037/0278-6133.17.1.63

McClernon, F. J., Kozink, R. V., Lutz, A. M., & Rose, J. E. (2009). 24-h smoking abstinence potentiates fMRI-BOLD activation to smoking cues in cerebral cortex and dorsal striatum. *Psychopharmacology*, *204*(1), 25–35. https://doi.org/10.1007/s00213-008-1436-9

McKee, S. A. (2009). Developing human laboratory models of smoking lapse behavior for medication screening. *Addiction Biology*, *14*(1), 99–107. https://doi.org/10.1111/j.1369-1600.2008.00135.x

McKee, S. A., Krishnan-Sarin, S., Shi, J., Mase, T., & O'Malley, S. S. (2006). Modeling the effect of alcohol on smoking lapse behavior. *Psychopharmacology*, *189*(2), 201–210. https://doi.org/10.1007/s00213-006-0551-8

Mckee, S. A., Weinberger, A. H., Shi, J., Tetrault, J., & Coppola, S. (2012). Developing and validating a human laboratory model to screen medications for smoking cessation. *Nicotine and Tobacco Research*, *14*(11), 1362–1371. https://doi.org/10.1093/ntr/nts090

Monsó, E., Campbell, J., Tønnesen, P., Gustavsson, G., & Morera, J. (2001). Sociodemographic predictors of success in smoking intervention. *Tobacco Control, 10*, 165-169. https://doi.org/10.1136/tc.10.2.165

Moustafa, A. A., Kéri, S., Somlai, Z., Balsdon, T., Frydecka, D., Misiak, B., & White, C. (2015). Drift diffusion model of reward and punishment learning in schizophrenia: Modeling and experimental data. *Behavioural Brain Research*, *291*, 147–154. https://doi.org/10.1016/j.bbr.2015.05.024

Mueller, E. T., Landes, R. D., Kowal, B. P., Yi, R., Stitzer, M. L., Burnett, C. A., & Bickel, W. K. (2009). Delay of smoking gratification as a laboratory model of relapse: Effects of incentives for not smoking, and relationship with measures of executive function. *Behavioural Pharmacology*, *20*(5–6), 461–473. https://doi.org/10.1097/FBP.0b013e3283305ec7

O'Doherty, J. P. (2004). Reward representations and reward-related learning in the human brain: Insights from neuroimaging. *Current Opinion in Neurobiology*, *14*(6), 769–776. https://doi.org/10.1016/j.conb.2004.10.016

Parkinson, J. A., Dalley, J. W., Cardinal, R. N., Bamford, A., Fehnert, B., Lachenal, G., Rudarakanchana, N., Halkerston, K. M., Robbins, T. W., & Everitt, B. J. (2002). Nucleus accumbens dopamine depletion impairs both acquisition and performance of appetitive Pavlovian approach behaviour: Implications for mesoaccumbens dopamine function. *Behavioural Brain Research*, *137*(1–2), 149–163. https://doi.org/10.1016/S0166-4328(02)00291-7

Pechtel, P., Dutra, S. J., Goetz, E. L., & Pizzagalli, D. A. (2013). Blunted reward responsiveness in remitted depression. *Journal of Psychiatric Research*, *47*(12), 1864–1869. https://doi.org/10.1016/j.jpsychires.2013.08.011

Pedersen, M. L., Frank, M. J., & Biele, G. (2017). The drift diffusion model as the choice rule in reinforcement learning. *Psychonomic Bulletin and Review*, *24*(4), 1234–1251. https://doi.org/10.3758/s13423-016-1199-y

Peechatka, A. L., Whitton, A. E., Farmer, S. L., Pizzagalli, D. A., & Janes, A. C. (2015). Cigarette craving is associated with blunted reward processing in nicotine-dependent smokers. *Drug and Alcohol Dependence*, *155*, 202–207. https://doi.org/10.1016/j.drugalcdep.2015.07.015

Perez, X. A., Ly, J., McIntosh, J. M., & Quik, M. (2012). Long-term nicotine exposure depresses dopamine release in nonhuman primate nucleus accumbens. *Journal of Pharmacology and Experimental Therapeutics*, *342*(2), 335–344. https://doi.org/10.1124/jpet.112.194084

Pergadia, M. L., Der-Avakian, A., D'Souza, M. S., Madden, P. A. F., Heath, A. C., Shiffman, S., … Pizzagalli, D. A. (2014). Association between nicotine withdrawal and reward

responsiveness in humans and rats. *JAMA Psychiatry*, *71*(11), 1238–1245. https://doi.org/10.1001/jamapsychiatry.2014.1016

Pessiglione, M., Seymour, B., Flandin, G., Dolan, R. J., & Frith, C. D. (2006). Dopamine-dependent prediction errors underpin reward-seeking behaviour in humans. *Nature*, *442*(7106), 1042–1045. https://doi.org/10.1038/nature05051

Pizzagalli, D. A., Goetz, E., Ostacher, M., Iosifescu, D. V., & Perlis, R. H. (2008). Euthymic Patients with Bipolar Disorder Show Decreased Reward Learning in a Probabilistic Reward Task. *Biological Psychiatry*, *64*(2), 162–168. https://doi.org/10.1016/j.biopsych.2007.12.001

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

Pizzagalli, D. A., Jahn, A. L., & O'Shea, J. P. (2005). Toward an objective characterization of an anhedonic phenotype: A signal-detection approach. *Biological Psychiatry*, *57*(4), 319–327. https://doi.org/10.1016/j.biopsych.2004.11.026

Powell, J., Dawkins, L., & Davis, R. E. (2002). Smoking, reward responsiveness, and response inhibition: tests of an incentive motivational model. *Biological Psychiatry*, *51*(2), 151–163. https://doi.org/10.1016/S0006-3223(01)01208-2

Powell, J. H., Pickering, A. D., Dawkins, L., West, R., & Powell, J. F. (2004). Cognitive and psychological correlates of smoking abstinence, and predictors of successful cessation. *Addictive Behaviors*, *29*(7), 1407–1426. https://doi.org/10.1016/j.addbeh.2004.06.006

Rafful, C., García-Rodríguez, O., Wang, S., Secades-Villa, R., Martínez-Ortega, J. M., & Blanco, C. (2013). Predictors of quit attempts and successful quit attempts in a nationally representative sample of smokers. *Addictive Behaviors*, *38*(4), 1920–1923. https://doi.org/10.1016/j.addbeh.2012.12.019

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review, 85*(2), 59-108. http://dx.doi.org.ezp-prod1.hul.harvard.edu/10.1037/0033-295X.85.2.59

Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Computation*, *20*(4), 873–922. https://doi.org/10.1162/neco.2008.12-06-420

Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion Decision Model: Current Issues and History. *Trends in Cognitive Sciences*, *20*(4), 260–281. https://doi.org/10.1016/j.tics.2016.01.007

Scharf, D., & Shiffman, S. (2004). Are there gender differences in smoking cessation, with and without bupropion? Pooled- and meta-analyses of clinical trials of Bupropion SR. *Addiction*, *99*(11), 1462–1469. https://doi.org/10.1111/j.1360-0443.2004.00845.x

Schultz, W. (2002). Getting formal with dopamine and reward. *Neuron*, *36*(2), 241–263. https://doi.org/10.1016/S0896-6273(02)00967-4

Smit, E. S., Hoving, C., Schelleman-Offermans, K., West, R., & de Vries, H. (2014). Predictors of successful and unsuccessful quit attempts among smokers motivated to quit. *Addictive Behaviors*, *39*(9), 1318–1324. https://doi.org/10.1016/j.addbeh.2014.04.017

Smith-Roe, S. L., & Kelley, A. E. (2000). Coincident activation of NMDA and dopamine D1 receptors within the nucleus accumbens core is required for appetitive instrumental learning. *Journal of Neuroscience*, *20*(20), 7737–7742. https://doi.org/10.1523/jneurosci.20-20-07737.2000

Stapleton, J. (1998). Cigarette smoking prevalence, cessation and relapse. *Statistical Methods in Medical Research*, *7*, 187–203. https://doi.org/10.1191/096228098671391775

Swan, G. E., Jack, L. M., & Ward, M. M. (1997). Subgroups of smokers with different success rates after use of transdermal nicotine. *Addiction*, *92*(2), 207–218. https://doi.org/10.1111/j.1360-0443.1997.tb03653.x

Sweitzer, M. M., Denlinger, R. L., & Donny, E. C. (2013). Dependence and withdrawal-induced craving predict abstinence in an incentive-based model of smoking relapse. *Nicotine and Tobacco Research*, *15*(1), 36–43. https://doi.org/10.1093/ntr/nts080

Tricomi, E. M., Delgado, M. R., & Fiez, J. A. (2004). Modulation of Caudate Activity by Action Contingency. *Neuron*, *41*, 281–292. https://doi.org/10.1016/S0896-6273(03)00848-1

U.S. Department of Health and Human Services, Centers for Disease Control and Prevention. (2014). The health consequences of smoking–50 years of progress: A Report of the Surgeon General. Retrieved from: https://www.surgeongeneral.gov/library/reports/50-years-of-progress/full-report.pdf

U.S. Department of Health and Human Services, Centers for Disease Control and Prevention. (2001). The health consequences of smoking: Women and smoking. Retrieved from: https://www.cdc.gov/mmwr/preview/mmwrhtml/rr5112a4.htm

U.S. Department of Health and Human Services, Centers for Disease Control and Prevention. (1990). The health benefits of smoking cessation (DHHS Publication No. (CDC) 90-8516). Retrieved from: https://www.cdc.gov/mmwr/preview/mmwrhtml/00001801.htm

Versace, F., Engelmann, J. M., Robinson, J. D., Jackson, E. F., Green, C. E., Lam, C. Y., … Cinciripini, P. M. (2014). Prequit fMRI Responses to pleasant cues and cigarette-related

cues predict smoking cessation outcome. *Nicotine & Tobacco Research*, *16*(6), 697–708. https://doi.org/10.1093/ntr/ntt214

Versace, F., Lam, C. Y., Engelmann, J. M., Robinson, J. D., Minnix, J. A., Brown, V. L., & Cinciripini, P. M. (2011). Beyond cue reactivity: Blunted brain responses to pleasant stimuli predict long-term smoking abstinence. *Addiction Biology*, *17*(6), 991–1000. https://doi.org/10.1111/j.1369-1600.2011.00372.x

Volkow, N. D., & Morales, M. (2015). The brain on drugs: From reward to addiction. *Cell*, *162*(4), 712–725. https://doi.org/10.1016/j.cell.2015.07.046

Wang, K. S., Smith, D. V., & Delgado, M. R. (2016). Using fMRI to study reward processing in humans: Past, present, and future. *Journal of Neurophysiology*, *115*(3), 1664–1678. https://doi.org/10.1152/jn.00333.2015

Waters, A. J., Shiffman, S., Sayette, M. A., Paty, J. A., Gwaltney, C. J., & Balabanis, M. H. (2003). Attentional bias predicts outcome in smoking cessation. *Health Psychology*, *22*(4), 378–387. https://doi.org/10.1037/0278-6133.22.4.378

Westman, E. C. (1997). Smoking Behavior on the first day of a quit attempt predicts long-term abstinence. *Archives of Internal Medicine*, *157*(3), 335–340. https://doi.org/10.1001/archinte.1997.00440240101015

White, C. N., Ratcliff, R., Vasey, M. W., & McKoon, G. (2010). Anxiety Enhances Threat Processing Without Competition Among Multiple Inputs: A Diffusion Model Analysis. *Emotion*, *10*(5), 662–677. https://doi.org/10.1037/a0019474

Wiecki, T. V., Sofer, I., & Frank, M. J. (2013). HDDM: Hierarchical Bayesian estimation of the Drift-Diffusion Model in Python. *Frontiers in Neuroinformatics*, *7*(14), 1–10. https://doi.org/10.3389/fninf.2013.00014

Wilson, S. J., Smyth, J. M., & MacLean, R. R. (2014). Integrating ecological momentary assessment and functional brain imaging methods: New avenues for studying and treating tobacco dependence. *Nicotine and Tobacco Research*, *16*(suppl 2), 102–110. https://doi.org/10.1093/ntr/ntt129

World Health Organization (2011). *Assessment of the economic costs of smoking.* Retrieved from: https://apps.who.int/iris/handle/10665/44596

Xue, S., Behnood-Rod, A., Wilson, R., Wilks, I., Tan, S., & Bruijnzeel, A. W. (2020). Rewarding Effects of Nicotine in Adolescent and Adult Male and Female Rats as Measured Using Intracranial Self-stimulation. *Nicotine and Tobacco Research*, *22*(2), 172–179. https://doi.org/10.1093/ntr/nty249

Appendix A: Tables

Table 1. *Demographic and smoking characteristics*

Variable	M *(SD)*, [n]		Statistics
	0-minute	**50-minute**	
Age	43.69 *(10.59)*	40.64 (*10.88*)	$t = 1.27, p = 0.209$
Gender			
Female	[14]	[11]	Fisher's exact = 0.228
Male	[22]	[33]	
Education*			
Less than high school	[5]	[4]	
High school or GED	[13]	[9]	$X^2 = 4.11, p = 0.250$
Some college	[10]	[19]	
College or higher	[6]	[11]	
FTND	5.83 *(1.94)*	4.93 (*2.33*)	$t = 1.86, p = 0.067$
Cigs per day**	17.79 *(5.44)*	16.50 (7.52)	$t = 0.85, p = 0.398$
Years of smoking	24.03 *(11.52)*	20.91 *(11.09)*	$t = 1.23, p = 0.222$
# of cigs before PRT visit	5.28 (4.12)	4.32 (3.08)	*t = 1.19, p = 0.237*

*N = 3 missing data
**N = 1 missing data
FTND: Fagerstrom Test for Nicotine Dependence

Table 2. *2-way ANOVA group*block interaction and 3-way ANOVA group*block*stimulus results for standard PRT variables*

	0-Minute		50-Minute				
PRT Variable	M	SD	M	SD	F	P-Value	Partial eta^2
Block 1 Response Bias	0.14	0.16	0.14	0.17			
Block 2 Response Bias	0.16	0.21	0.18	0.20	0.56	0.574	0.007
Block 3 Response Bias	0.21	0.16	0.25	0.23			
Block 1 Discriminability	0.42	0.21	0.59	0.31			
Block 2 Discriminability	0.50	0.29	0.68	0.29	0.15	0.859	0.002
Block 3 Discriminability	0.51	0.29	0.71	0.32			
Block 1 Reaction Time (Rich)	683.36	211.35	658.23	268.85			
Block 2 Reaction Time (Rich)	599.30	158.79	573.57	220.61			
Block 3 Reaction Time (Rich)	602.47	192.94	552.41	189.52	0.28	0.755	0.007
Block 1 Reaction Time (Lean)	723.58	224.39	694.24	287.80			
Block 2 Reaction Time (Lean)	664.67	198.78	647.01	242.42			
Block 3 Reaction Time (Lean)	675.74	230.59	622.49	207.69			

Table 3. *Cohen's D calculations for standard and HDDM PRT Variables*

	0-Minute		50-Minute			
PRT Variable	M	SD	M	SD	SD_{pooled}	Cohen's D
Standard Parameters						
Block 1 Response Bias	0.14	0.16	0.14	0.17	0.16	0.02
Block 2 Response Bias	0.16	0.21	0.18	0.20	0.21	0.08
Block 3 Response Bias	0.21	0.16	0.25	0.23	0.20	0.23
Block 1 Discriminability	0.42	0.21	0.59	0.31	0.39	0.44
Block 2 Discriminability	0.50	0.29	0.68	0.29	0.29	0.63
Block 3 Discriminability	0.51	0.29	0.71	0.32	0.30	0.66
HDDM Parameters						
Drift rate	0.79	0.09	1.21	0.08	0.08	5.07
Starting bias	0.56	0.01	0.56	0.01	0.01	0.77

Appendix B: Figures

Figure 1. *Diagram of PRT stimuli (Pizzagalli, Jahn, and O'Shea, 2005)*

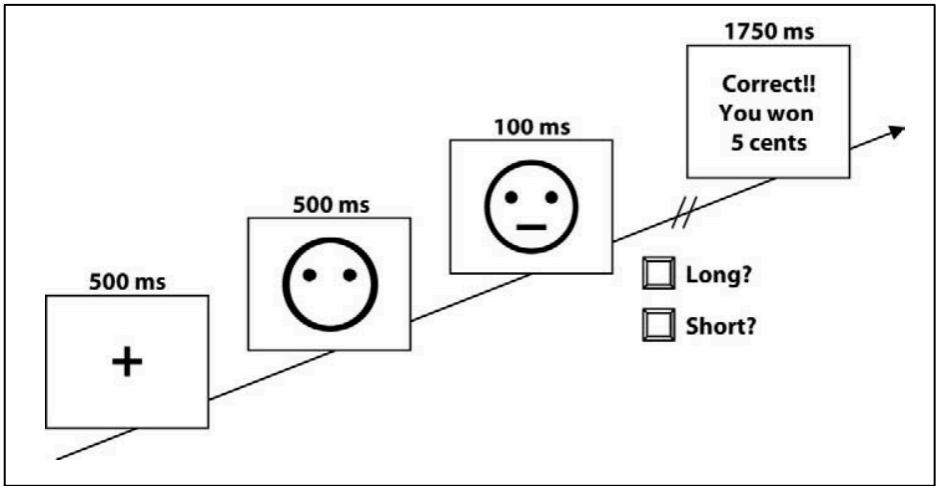

Figure 2a. *Posterior distribution of group means for drift-rate during the PRT*

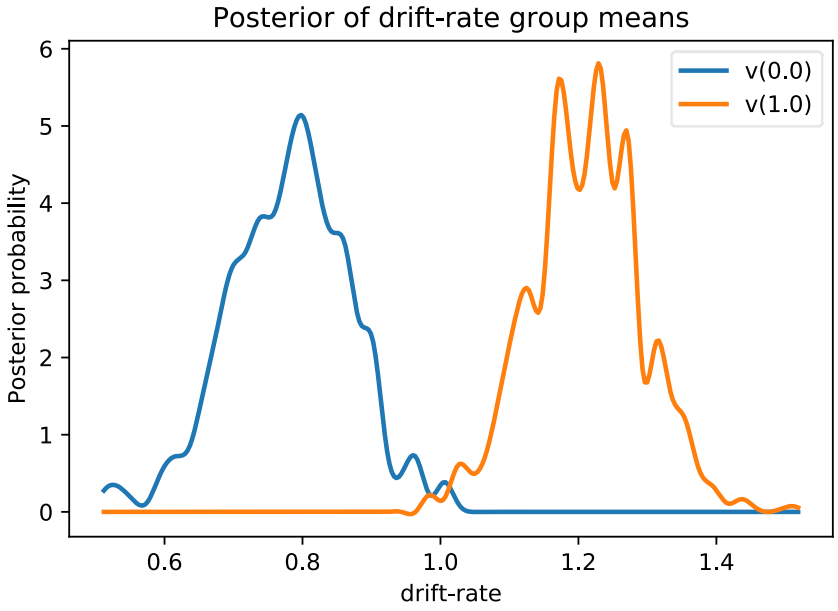

Figure 2b. *Posterior distribution of group means for starting bias during the PRT*