

Neural mechanisms of affective instability in substance use.

by

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Bachelor of Science (Honours), University of Winnipeg, 2007

Bachelor of Arts, University of Winnipeg, 2007

Master of Science, University of Victoria, 2010

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Supervisory Committee

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Abstract

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Substance use disorders (SUDs) are a growing concern in today's society. Substantial research has advanced our understanding of how cognitive control, reward processing, and emotional difficulties may contribute to the development and maintenance of SUDs; however, the impact of affective instability in SUDs has received limited attention. I sought to examine how different dimensions of affective instability interact to increase substance misuse, and to investigate the impact of affective instability and substance use on neural mechanisms of reward and emotion processing. Specifically, I was interested in two event-related potential (ERP) components, the reward positivity and the late positive potential (LPP), which respectively reflect the neural mechanisms of reward and emotion processing. Toward this end, I recorded the ongoing electroencephalogram (EEG) from undergraduate students as they navigated two T-maze tasks in search of rewards. Further, one of the tasks included neutral, pleasant, and unpleasant pictures from the International Affective Picture System (IAPS). Participants also completed several questionnaires pertaining to substance use and personality. A principal components analysis (PCA) revealed a factor related to affective instability, which I named reactivity. This factor significantly predicted increased substance use. Interestingly, individuals reporting higher levels of affective reactivity also displayed a larger reward positivity following stimuli with emotional content. The

current study identified a group of high-risk substance users characterized by greater levels of affective reactivity and increased reward processing. It is my hope that these results further elucidate the complexities of SUDs and help to create efficacious, individually-tailored treatment programs for those struggling with SUDs.

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Dedication

To Caius, *my greatest blessing and inspiration.*

Introduction

The year 2016 saw Canada facing a “fentanyl crisis” with the number of overdoses of fentanyl and carfentanil increasing at an alarming rate. In response, Canada’s Health Minister announced a joint action plan in order to address the opioid crisis in Canada (Ireland, 2017). Unfortunately, fentanyl is just the latest substance in Canada’s ongoing struggle with substance use. In 2012, Statistics Canada reported 21.6%, or approximately 6 million Canadians struggle with a substance use disorder (SUD) during their lifetime (Pearson, Janz, & Ali, 2012). SUDs have a significant economic burden on public services including health care and law enforcement, as well as lost productivity in the workplace. In 2002, the estimated total cost of substance abuse in Canada was \$39.8 billion (Rehm et al., 2007). Perhaps more important than the extreme financial costs are the psychological, physical, and social consequences associated with SUDs. SUDs can affect every aspect of an individual’s life; they put immense strain on families and relationships, they can result in the loss of employment and financial stability, and they can cause physical health to deteriorate and significantly reduce an individual’s quality and length of life (American Psychiatric Association, 2013). Legal substances such as alcohol and tobacco have the widest spread use and the most damaging effects to individuals and society (Rehm, Taylor, & Room, 2006).

Substance use and associated difficulties related to misuse of substances has long been recognized as a serious and complicated issue. In fact, we continue to strive for a better understanding at the most basic level – how to best define disordered use of substances. The DSM-5 discontinued classifying problematic use of substances as abuse or dependence because of growing recognition that disordered use of substances is not unidimensional and is better represented along a continuum of severity (Jones, Gill, & Ray, 2012). A defining feature of SUDs

includes problematic cognitive, behavioural, and physiological symptoms that an individual experiences due to ongoing use of a substance. The DSM-5 posits four groupings of symptoms: impaired control, social impairment, risky use, and pharmacological criteria (i.e. tolerance and withdrawal). The diagnosis of a SUD is substance-specific and severity is based on the number of symptoms endorsed, ranging from mild (2-3 symptoms) to severe (6 or more symptoms) (American Psychiatric Association, 2013).

A number of theories have been proposed to explain the development and maintenance of SUDs. Broadly, theories have either focused on individuals or populations. While theories at both levels are invaluable to society's understanding, prevention, and treatment of SUDs, theories at the individual level attempt to identify and explain the process of why certain individuals develop a SUD while others do not. At the individual level, a variety of theories include automatic processing theories, reflective choice theories, goal-focused theories, process-of-change theories and biological theories (West, 2013). At the centre of these theories is a loss of control over use of the substance (Redish, Jensen, & Johnson, 2008). Traditionally, evidence for loss of control was inferred from behaviour. In particular, animal models mimicking loss of control over drug use date back to the late 1960s (Wikler & Pescor, 1967). Since the invention of neuroimaging techniques, extensive research has focused on exploring the neurobiology behind this loss of control in humans. Yet, although important advances have been made in understanding the neurocircuitry involved in how drugs of abuse 'usurp' the cognitive control system, criticism has included a lack of integration on how emotional processing may mediate the development and maintenance of addiction (Cheetham et al., 2010). The current dissertation uses electrophysiological and self-report measures to examine the roles that emotional processing and cognitive control have in substance use.

Substance Use Disorders and Emotions

The relationship between SUDs and emotional difficulties is well established. Affective psychopathologies such as depression and anxiety disorders (e.g., panic disorder) have high rates of comorbid SUDs (American Psychiatry Association, 2013). Individuals diagnosed with SUDs have demonstrated deficits in their ability to express and experience emotions (Arcos et al., 2008). The connection between emotions and substance use is multifaceted. A recent review found unique roles for positive and negative affect in the initiation and maintenance of SUDs (Cheetham, Allen, Yücel, & Lubman, 2010). It has been argued that individuals experiencing negative emotions may begin using substances in order to distract from, cope with, or improve unpleasant feelings such as anxiety, sadness, and pain (Cheetham et al., 2010; Measelle, Stice, & Springer, 2006). Alternatively, once an individual becomes physically dependent on a substance, use may be maintained by a desire to avoid the negative affective state associated with withdrawal (Kassel et al., 2007). By ameliorating negative emotions, including symptoms of withdrawal, substance use is strengthened through negative reinforcement (Koob & Moal, 2008). Positive emotions have also been suggested to play a role in SUDs. Individuals who experience greater levels of positive affect are more likely to engage in risky behaviour and may seek out substances for their hedonic properties (Cheetham et al., 2010). Many substances of abuse have been described as producing feelings of euphoria, or increasing positive emotion (Jaffe & Jaffe, 1989). It has been argued that the positive effects experienced following substance use act to maintain use through positive reinforcement (Kober, 2014).

Complicating research regarding emotions and SUDs are the numerous theories that attempt to define and explain the construct of emotion (see Mulligan & Scherer, 2012); it is arguably one of the most disagreed upon concepts in psychology today. Generally, the term

'emotion' is understood to describe relatively brief psychological states that range in valence (positive/negative) and intensity (weak/strong). Our understanding of emotion has been shaped by numerous disciplines, including philosophy, psychology, and more recently, neuroscience. Emotion has been described through a number of observable components including: language, physiological responses (i.e. accelerated heart rate, dilated pupils), behaviours, motor responses, and subjective experiences (Lang, 2010; Mulligan & Scherer, 2012). From an evolutionary perspective, the ability of emotions to motivate and guide behaviour makes them necessary for survival (Kelley, 2005).

While the definition of emotion continues to be debated, it is further confounded by the fact that it is often used interchangeably with the term 'affect'. According to Renaud and Zacchia (2012), affect is defined as a 'sensorial experience in response to internal or external stimuli that is expressed with physiologic and motor responses'. In other words, affect is a rapid, conscious, subjective emotional experience in response to stimuli. Emotion, on the other hand, is a 'complex set of affects with mental representations generated in association with previous memories and bodily experiences'. For the purpose of this dissertation, the term affect will be used in order to differentiate short-term emotional changes from long-standing, complex emotions that involve integration of an individual's prior experiences or memories.

A key area of interest in emotion research lies in emotional regulation, which refers to the ability of an individual to adaptively modulate or control their affective responses to stimuli or situations. Specifically, the construct of emotional regulation encompasses the ability to influence the type of emotion experienced, as well as the intensity and duration of the emotion (Gross & Thompson, 2007). Cole, Michel, and Teti (1994) suggested that access to a range of emotions, flexible modulation of intensity and duration of emotions, and the ability to transition between

different emotions are important dimensions when characterizing emotional regulation. The relationship between emotional regulation and psychological difficulties often lies in the inability of an individual to regulate their emotional response (i.e. emotional dysregulation), which is a critical component of psychopathologies including mood and substance-related disorders (Berking & Wupperman, 2012).

At the centre of an inability to regulate emotions, or emotional dysregulation, is the concept of affective instability. Affective instability has traditionally been conceptualized and defined as a symptom or difficulty observed in individuals with borderline personality disorder (BPD) (Nica & Links, 2009). Recently, researchers and clinicians have begun to recognize the presence of affective instability in a number of other clinical disorders (i.e. attention-deficit hyperactivity disorder, bipolar disorder, major depressive disorder, eating disorders, post-traumatic stress disorder, and anxiety disorders) (Renaud & Zacchia, 2012; Marwaha et al., 2014). Despite evidence of affective instability being an important symptom in many psychological disorders associated with co-morbid substance misuse, there has been very little research examining the role of affective instability in SUDs.

Unfortunately, the term affective instability has been poorly defined, likely due in part to interchangeable terms (i.e. *emotion* vs. *affect* vs. *mood*; *instability* vs. *reactivity* vs. *lability*). Two recent reviews have sought to propose a cohesive definition of affective instability. Renaud and Zacchia (2012) defined affective instability as an “inherited/temperamental trait modulated by developmental experiences; influences emotional experience and predisposes to mood pathology; dimensions include affective valence, affect amplitude, low reactivity threshold to environmental triggers, rapid affect shifting with random patterning, and dyscontrolled regulation of emotions”. Marwaha and colleagues (2014) offered a simpler definition: “rapid oscillations of intense affect,

with a difficulty in regulating these oscillations or their behavioural consequences”. Further complicating the quest for a unified definition of affective instability is whether emotional dysregulation is a dimension of affective instability, or alternatively whether affective instability is a component of emotional dysregulation. Renaud and Zacchia (2012) and Marwaha (2014) both proposed that difficulty regulating emotions constitutes a dimension of affective instability; however, in the BPD literature, affective instability, along with emotion sensitivity, is conceptualized as a key component of emotional dysregulation (see Carpenter & Trull, 2013 for review). An integrative review recommended factors related to emotional sensitivity should be considered separately from emotional regulation as the former determines the onset of emotional processing, whereas the latter determines the offset (Koole, 2009). Emotional regulation involves cognitive and behavioural responses to emotional experiences (Berking & Wupperman, 2012; Gross & Thompson, 2007; Sheppes, Suri, & Gross, 2015) and is arguably a more complex, malleable concept than dimensions of affective instability.

Defining and measuring affective instability within the context of clinical disorders is complicated by the fact that a number of other symptoms and difficulties contribute to the constellation of any given psychological disorder. For example, affective instability is considered a core difficulty in BPD, but individuals with BPD also typically demonstrate identity disturbance, marked interpersonal difficulties, and recurrent suicidal behaviours (American Psychiatric Association, 2013). Research investigating affective instability has focused on its role in clinical disorders, perhaps because of a traditionally categorical approach to defining and diagnosing mental health disorders. This approach has been criticized due to the fact that categories are arbitrary as there is no clear distinction between problematic and disordered behaviour (i.e. it is unclear when personality traits become disordered) (Widiger, 1993). There is a great deal of

support for the theory that personality traits are continuous and recently it has been argued that clinicians should adopt a dimensional approach to diagnosing personality disorders (Krueger, Derringer, Markon, Watson, & Skodol, 2011; Morey et al., 2006; Suzuki, Samuel, Pahlen, & Krueger, 2015). The dimensional approach posits that personality traits exist along a continuum and only become clinically significant when their expression is extreme, rigid, and maladaptive.

With the publication of the DSM-5 came acknowledgment of the importance of considering personality disorders from a dimensional perspective. An alternative model for conceptualizing personality included in DSM-5 identifies five trait domains and 25 trait facets which have the potential to be pathological at the extreme ends of expression (American Psychiatric Association, 2013). In this model, emotional stability is a key domain, under which the trait facet of emotional lability falls. Despite evidence that these are important traits, an understanding of how these traits are expressed in non-personality disordered individuals is limited. The DSM-5 proposes that a thorough understanding of an individual's personality functioning can provide information regarding treatment planning and predicting the course and outcome of individuals with SUDs (American Psychiatric Association, 2013). Hasin and colleagues (2011) found that BPD is a strong predictor of persistence of SUDs. They recommended the relationship of personality traits associated with BPD, such as emotional instability, and SUDs should be investigated in order to reach a deeper understanding regarding what aspects of BPD might increase risk for comorbid SUDs. Research has failed to demonstrate affective instability is specific to BPD, supporting the idea that it is indeed a transdiagnostic construct (Ebner-Priemer, Santangelo & Bohus, 2016). Ebner-Priemer and colleagues propose a need for future research to look at basic physiological processes in order to improve our understanding of dynamic affective mechanisms. If affective instability is conceptualized as a trait, it would exist on a continuum

between normative and pathological expression, yet research on the normative end of the spectrum is lacking.

Despite affective instability being such an important psychological construct, it is complicated to measure. A recent systematic review determined that there was not a single measure that comprehensively assesses affective instability and therefore recommended a combination of current measures for accurate assessment (Marwaha et al., 2014). This dissertation focuses on components of affective instability that impact the initial experience of affect and does not extend to include emotional regulation, which occurs after the initial emotion has been experienced and typically requires effortful cognitive or behavioural strategies. Two core dimensions of affective instability include the *intensity* with which an individual experiences their emotions, and the *frequency* with which an individual's affective experience changes. These dimensions have been commonly assessed by self-report questionnaires developed to evaluate individuals' subjective experience of affect intensity and lability: the Affect Intensity Measure (AIM) (Larsen & Diener, 1987) and the Affective Lability Scale (ALS) (Harvey, Greenberg, & Serper, 1989) (Table 1). Both measures have been extensively used to study affective intensity and lability in non-clinical (Botella et al., 2011; Pearson, Lawless, Brown, & Bravo, 2015; Veilleux, Skinner, Reese, & Shaver; Xu, Martinez, Hoof, Eljuri, & Arciniegas, 2016) and clinical populations (see Marwaha et al., 2014 for review).

Studies looking at the relationship between affect intensity and lability and SUDs are relatively sparse. Thorberg and Lyvers (2006) found that individuals with a history of addiction reported higher levels of affect intensity than non-addicted individuals. In a sample of individuals in treatment for SUDs, affective lability was associated with alcohol dependence (Simons, Oliver, Gaher, Ebel, & Brummels, 2005). Similarly, college students reporting greater affective lability

were more likely to develop difficulties with alcohol dependence (Simons et al., 2009). Affective lability has also been found to significantly correlate with alcohol and cannabis use disorders in individuals with Bipolar Disorder (Lagerberg et al., 2017).

Another component related to affective intensity and lability, which has not been traditionally considered in the affective instability literature, is that of *urgency*. Urgency has been defined as a “disposition to engage in rash action when experiencing extreme positive and negative affect” and has been researched with regard to increased rates of substance use (Cyders & Smith, 2007, 2008). The construct of urgency arose from research focused on impulsivity and was parsed into positive and negative urgency which are included as factors in the UPPS-P Impulsive Behavior Scale (Cyders et al., 2007; Whiteside, Lynam, Miller, & Reynolds, 2005; Whiteside & Lynam, 2001). Positive urgency measures the likelihood that an individual will act impulsively when experiencing positive emotions, whereas negative urgency refers to the tendency to act rashly in response to distress (Table 1). Both positive and negative urgency are associated with higher risk of substance misuse. A recent meta-analysis found that among traits of impulsivity, negative urgency was the strongest predictor of problematic alcohol consumption (Coskunpinar, Dir, & Cyders, 2013). Individuals reporting higher levels of positive urgency were found to consume a greater quantity of alcohol following a high-activation positive mood induction (Dinc & Cooper, 2015). Only one study to date has looked at the relationship between urgency and affective lability and concluded that negative urgency may mediate the effects of lability on problematic alcohol use (Coskunpinar, Dir, Karyadi, Koo, & Cyders, 2013). Taken together, the AIM, ALS, and positive and negative urgency assess important aspects of affective instability: the intensity with which emotions are experienced, the speed at which emotions change, and how responsive an individual is to their emotions.

	<i>Definition</i>	<i>Measure</i>	<i>Example Question</i>
<i>Affective Instability</i>	Rapid oscillations of intense affect, with a difficulty in regulating these oscillations or their behavioural consequences (Marwaha et al., 2014; also see Renaud & Zacchia, 2012)	Multidimensional and requires multiple self-report questionnaires to assess.	See below for example questions from self-report questionnaires that assess specific dimensions of affective instability.
<i>Affect Intensity</i>	A stable individual difference in the typical intensity with which individuals experience their emotions (Larsen & Diener, 1985)	Affect Intensity Measure (AIM) (Larsen & Diener, 1987)	‘When something good happens, I am usually much more jubilant than others.’
<i>Affective Lability</i>	Rapid shifts in outward emotional expressions (Look et al., 2010)	Affective Lability Scale (ALS) (Harvey et al., 1989), Affective Lability Scale – 18 (ALS-18) (Look et al., 2010)	‘I switch back and forth between being extremely energetic and having so little energy that it’s a huge effort just to get where I’m going’
<i>Negative Urgency</i>	The tendency to engage in rash action in response to extreme negative affect (Cyders & Smith, 2008)	UPPS-P Impulsive Behavior Scale (UPPS-P) (Cyders et al., 2007)	‘When I feel bad, I will often do things I later regret in order to make myself feel better now’
<i>Positive Urgency</i>	The tendency to engage in rash action in response to extreme positive affect (Cyders & Smith, 2008)	UPPS-P Impulsive Behavior Scale (UPPS-P) (Cyders et al., 2007)	‘When overjoyed, I feel like I can’t stop myself from going overboard.’

Table 1. Definitions of affective dimensions, self-report measures to assess each dimension, and an example item from each questionnaire.

Substance Use Disorders and Neural Mechanisms

In contrast to limited research looking at the relationship between affective instability and SUDs, there has been substantial research examining the neural mechanisms of SUDs. Perhaps one of the most essential discoveries was the impact drugs of abuse have on the dopamine (DA) system, particularly on neural circuits involved with reward processing, cognitive control, and motivation (Baler & Volkow, 2006). Early neuropharmaceutical research demonstrated the midbrain DA system (MDS) plays a role in the positive reinforcing effects of all addictive substances including alcohol, nicotine, cocaine, amphetamine, and heroin (Koob & Le Moal, 1997; Volkow & Baler, 2014). DA has an impact on every stage of substance use – the initial rewarding experience, maintenance of addiction, and relapse following a period of abstinence (Di Chara & Ssareo, 2007). The initial pharmacological response of substances of abuse cause an immediate and exaggerated DA response, resulting in stronger reinforcement and learned associations between the release of DA and the environmental trigger (Verrico et al., 2013). Thus, by causing changes in the MDS, substances of abuse directly impact areas of the brain responsible for cognitive control and reinforcement learning, leading to a loss of control over use of the substance (Volkow & Baler, 2014).

Individuals can learn from their environment by processing feedback, either positive or negative, in response to different actions, choices, or behaviours. Basic reinforcement learning theories propose that we monitor our environment and shape our actions through receiving rewards and ‘trial and error’ learning. By learning from positive and negative feedback, we can modify our behaviour in order to maximize rewards. One model of reinforcement learning, the actor-critic temporal-difference method (TD), appeals to psychological and biological theories because of its biological plausibility. In this model, the “actor” selects actions, while the “critic” evaluates the

results and verifies whether things have gone better or worse than expected. These critiques generate temporal difference errors (TDEs): positive TDEs signify that an event is better than expected, whereas negative TDEs signify that an event is worse than expected. Using this feedback, the system (i.e. 'actor') is then able to make necessary adjustments in order to improve the expected outcome (Sutton & Barto, 1998).

Interestingly, DA has been found to play a critical role in the ability to predict rewards and learn from feedback. DA neurons have been shown to increase their phasic firing rate in response to unexpected rewards. Once a reward is linked to a stimulus, rather than firing in response to the reward itself, this phasic burst of DA propagates to the stimulus representing a subsequent reward delivery. In other words, the phasic DA burst occurs in response to the earliest indication of a reward. On occasions where a stimulus predicting reward occurs, but there is no subsequent reward, a decrease in phasic DA firing is observed at the time the reward was expected (Ljungberg, Apicella, & Schultz, 1991; Schultz, Apicella, & Ljungberg, 1993). When a reward occurs as predicted, no significant change occurs in the firing rate of the DA neurons. These observations of phasic DA firing represent the difference between actual and expected rewards. The degree or size of the phasic DA burst serves as a measure of error in the prediction of the reward (i.e. large phasic bursts when rewards were unexpected or larger than anticipated) (Schultz, 2002).

The majority of dopaminergic neurons in the central nervous system are located in the MDS, which includes the ventral tegmental area (VTA) and substantia nigra (SN) (Chinta & Andersen, 2005). Interestingly, these areas have long been thought to play a role in reward processing and reward dependent learning (Schultz, Dayan, & Montague, 1997). In 1996, a theoretical model hypothesized that the phasic increases and decreases of DA from the MDS to cortical and subcortical structures deliver TDEs, which the model refers to as reward prediction

errors (RPEs) (Montague, Dayan, & Sejnowski, 1996; Bissonette & Roesch, 2016). These RPEs serve as an internal teaching signal, in turn enabling the system to learn from reinforcement or rewards (Montague, Hyman, & Cohen, 2004; Suri, 2002).

The activity and projections of the MDS have been extensively studied and the importance of DA has been well documented in a variety of brain structures and functions (Diana & Tepper, 2002). The VTA innervates the ventral striatum and prefrontal cortex through the mesostriatal and mesocortical pathways. DA neurons in the SN innervate the dorsal striatum through the nigrostriatal pathway (Bissonette & Roesch, 2016). The vast innervations result in the MDS playing a critical role in a number of human behaviours including emotional regulation, attention, motivation, reward processing, and cognitive control (Cools, 2008; Bissonette & Roesch, 2016). It follows that because the MDS has such extensive projections and affects so many neural areas, alterations in this system have been implicated in a number of psychiatric and neurological disorders, including SUDs (Bissonette & Roesch, 2016).

One area of frontal cortex that is strongly innervated by the MDS, in addition to a number of other subcortical and cortical regions, is the anterior cingulate cortex (ACC) (Paus, 2001; Dum & Strick, 1993). The ACC has been long believed to play an important role in cognitive control, or the ability to pursue a goal despite distractions or competing demands (Brown, 2017; Holroyd & Yeung, 2012; Shenhav et al., 2013). Although years of research have indicated that the ACC plays a critical role in cognitive control, its precise role continues to be debated. A theory rooted in reinforcement learning proposed that the ACC uses RPE signals carried by the MDS system to assess ongoing performance on a given task and make modifications as necessary. That is, phasic changes in DA (RPEs) communicate to the ACC whether events are going better or worse than expected and the ACC uses this information to modify its performance (Holroyd & Coles, 2002).

Recently, this theory has expanded basic principles of reinforcement learning into a hierarchical reinforcement learning (HRL) model in order to better encapsulate observations associated with the ACC. The HRL model proposed the ACC is more concerned with higher-level “options” rather than simple “primitive actions”. In this model, the ACC associates values with different tasks or goals and directs the basal ganglia to implement the task through more primitive actions. The ACC uses information from the environment to decide which tasks to perform, when to switch tasks, and how much effort is required in order to reach a goal (Holroyd & McClure, 2015; Holroyd & Yeung, 2012). In other words, according to the HRL-ACC theory, the ACC is responsible for selecting and motivating extended behaviours (Holroyd & Umemoto, 2016). Another recent integrative theory proposed the ACC estimates the expected value of control in order to determine whether it is worthwhile to assign cognitive control to a specific task and how much control should be invested (Shenhav, Botvinick, & Cohen, 2013). Within this model, the ACC acts to specify and monitor the amount of control dedicated toward a specific task or goal. According to these theories, ACC has a role in motivating behaviour by using information from the environment to assign value to certain behaviours. The ACC then allocates and implements cognitive control in order to perform goal-directed behaviours. Despite differences in the theories, there is agreement that the ACC uses positive and negative feedback to modify and motivate higher-order or goal-directed behaviour (Ebitz & Hayden, 2016).

Taken together, if substances of abuse act directly on the MDS by causing an exaggerated DA response, in turn they will create an unnaturally large positive RPE signal. That is, regardless of whether a substance was expected to be rewarding, a positive RPE will be produced, thereby reinforcing the behaviour of ingesting the substance. This contrasts with naturally occurring rewards that only produce positive RPE signals when the reward is unexpected. The positive RPE

is carried by the MDS to the ACC, teaching the system that previous behaviour (i.e. ingesting a substance) was more rewarding than expected. The ACC uses information carried by the MDS in the form of RPE signals to learn which behaviours are rewarding and worth performing. Furthermore, the positive RPE signal will propagate back in time to the first indication of a pending reward, meaning behaviours leading up to the use of the substance are reinforced. By acting on neural circuits associated with cognitive control, motivation, and goal-directed behaviours, substances of abuse are said to ‘usurp’ the cognitive control system (Hyman, 2007).

Emotions and Neuroimaging

As an understanding of the role emotional processing and regulation play in a number of psychological difficulties has grown, so have the scientific approaches and methods of studying emotional processes. In recent years, interest in the neuroscience of emotional processing and regulation has flourished. Much of the work in this area has been done with fMRI, but there are a growing number of studies examining the electrophysiological nature of emotional processes. The P300 and the late positive potential (LPP) are two event-related potential (ERP) components that have proven to be of interest when examining how emotional stimuli are processed. ERPs are brief neural responses in the ongoing electroencephalography (EEG) that directly result from a specific event (such as the appearance of an external stimulus).

The P300 is a broad positivity observed between 300 and 600 ms following stimulus presentation and is maximal at parietal electrode sites (Sutton, Braren, Zubin, & John, 1965). The P300 has been most extensively studied in ‘oddball tasks’ in which participants are instructed to pay attention to infrequent stimuli (Luck, 2012). In oddball tasks, the amplitude of the P300 is larger in response to infrequent in comparison to frequent stimuli, but P300 amplitude has also been demonstrated to be larger in response to target stimuli when probabilities are equated

(Duncan-Johnson & Donchin, 1977). The P300 is believed to be reflect attentional processes demanded by environmentally salient information. It has been argued that emotional stimuli are automatically processed as environmentally salient or task-relevant because of their intrinsic motivational significance. Going hand-in-hand with this notion is the observation that the amplitude of the P300 is increased following the presentation of emotional stimuli in comparison with neutral stimuli (see Hajcak, MacNamara, & Olvet, 2010; Hajcak, Weinberg, MacNamara, & Foti, 2012 for review).

The LPP is a sustained positive deflection following the presentation of pleasant and unpleasant stimuli that is absent or reduced following neutral stimuli. It is observed as having a similar onset and distribution as the P300 but extends for hundreds of milliseconds longer than the P300. From 300 to 1000 ms, it is maximal at centroparietal sites, but becomes more broadly distributed across superior sites after 1000 ms (Hajcak et al., 2012; Luck, 2012). Due to changes in distribution over time, the LPP is typically measured across multiple time windows. It is larger for more intense or arousing stimuli (Cuthbert, Schupp, Bradley, Birbaumer, & Lang, 2000; Schupp et al., 2000), does not habituate to repeated presentation of emotional stimuli, and appears to be a relatively stable individual trait (Codispoti, Ferrari, & Bradley, 2006). LPP amplitude is also larger in response to stimuli representative of objects that hold personal relevance or importance. For example, individuals with a spider phobia had enhanced LPPs in response to phobic-relevant pictures in comparison to individuals without a spider phobia (Michalowski, Pané-Farré, Löw, & Hamm, 2015; Scharmüller, Leutgeb, Schäfer, Köchel, & Schienle, 2011). It has also been demonstrated to be sensitive to individual differences relating to anxiety; pictures representing threatening stimuli elicited a larger LPP in highly anxious individuals (MacNamara & Hajcak, 2010; MacNamara, Kotov, & Hajcak, 2015; Richards, Holmes, Pell, & Bethell, 2013).

Despite the widespread use of the LPP as a measure of emotional processing, its functional significance and underlying neural substrates are relatively unknown. Two primary hypotheses have been proposed to explain the functional significance of the LPP (Brown et al., 2012). The enhanced perception hypothesis purports that the LPP represents a global or spatially non-specific temporary increase in attention that facilitates the processing of emotional stimuli. While the global inhibition hypothesis suggests the LPP reflects a global inhibition of visual representations following emotional stimuli that allows selective processing of emotional information. Brown and colleagues (2012) investigated these hypotheses in a series of experiments, and while their results were consistent with the global inhibition hypothesis, they were unable to conclusively reject or confirm either hypothesis. Liu and colleagues (2012) simultaneously recorded an ongoing EEG and fMRI in order to investigate the underlying neural structures responsible for producing the LPP. They determined that the LPP is generated and modulated by an extensive brain network comprised of subcortical and cortical structures associated with visual and emotional processing. Further, the valence of the emotional stimuli (i.e. pleasant or unpleasant) impacts which structures are activated and contribute to the modulation of LPP amplitude. Taken together, although the LPP is well established as a reliable electrophysiological marker of emotional processing, its specific functional significance and underlying neural substrates remain unclear.

In addition to influencing the amplitude of the P300 and LPP, emotional stimuli have also been demonstrated to increase the RPE. A recent fMRI study found that emotional stimuli, presented independently of a learning task, were associated with an enhanced response in the ventral striatum at the time of feedback delivery; this enhanced response was interpreted as a RPE signal, perhaps reflecting DA modulation of the ventral striatum (Watanabe, Sakagami, & Haruno,

2013). In this study, each trial of a probabilistic trial-and-error learning task began with presentation of an image of a fearful or neutral face. The investigators found greater activation in the ventral striatum when unexpected reward outcomes were presented following exposure to fearful faces in comparison to neutral faces. This effect remained after corrections were made for reward size and expected value. Through a psychophysiological interaction analysis, Watanabe and colleagues concluded that amygdala activation in response to emotional stimuli was functionally linked with RPE signals produced in the striatum. They interpreted the results as evidence that humans can utilize emotional information from the environment in order to maximize reward.

Substance Use Disorders and Neuroimaging

The impact of SUDs on the MDS and ACC may be evident in a component of the ERP. Specifically, it has been proposed that RPE signals are observable as an ERP component, referred to as the reward positivity (formerly or more commonly known as the feedback related negativity or FRN). The reward positivity is believed to measure the impact of phasic DA increases and decreases on the ACC (Holroyd & Coles, 2002; see also Walsh & Anderson, 2012). Traditionally, the reward positivity was believed to be driven by a negative deflection in the ERP in response to negative feedback or errors, but recent evidence has suggested it is produced by positive feedback or rewards (Holroyd et al., 2008; also see Proudfit, 2015). The reward positivity is typically measured as the difference in the ongoing EEG between positive and negative feedback in response to trial-and-error learning tasks (Figure 1) (Holroyd & Krigolson, 2007; Miltner et al., 1997; Sambrook & Goslin, 2015). It is characteristically observed approximately 250 ms following feedback and is maximal over front-central electrodes (Walsh & Anderson, 2012). A recent meta-analysis found compelling evidence that the reward positivity is indeed responsive to reward magnitude and likelihood, consistent with a neural electrophysiological marker of RPE signals

(Sambrook & Goslin, 2015). In addition, there is a wealth of evidence that the reward positivity is generated in the ACC, including results from source localization studies (Miltner et al., 1997), simultaneous EEG/fMRI recordings (Hauser et al., 2014, but see Foti, Weinberg, Dien, & Hajcak, 2011), and animal studies (Warren, Hyman, Seamans, & Holroyd, 2015).

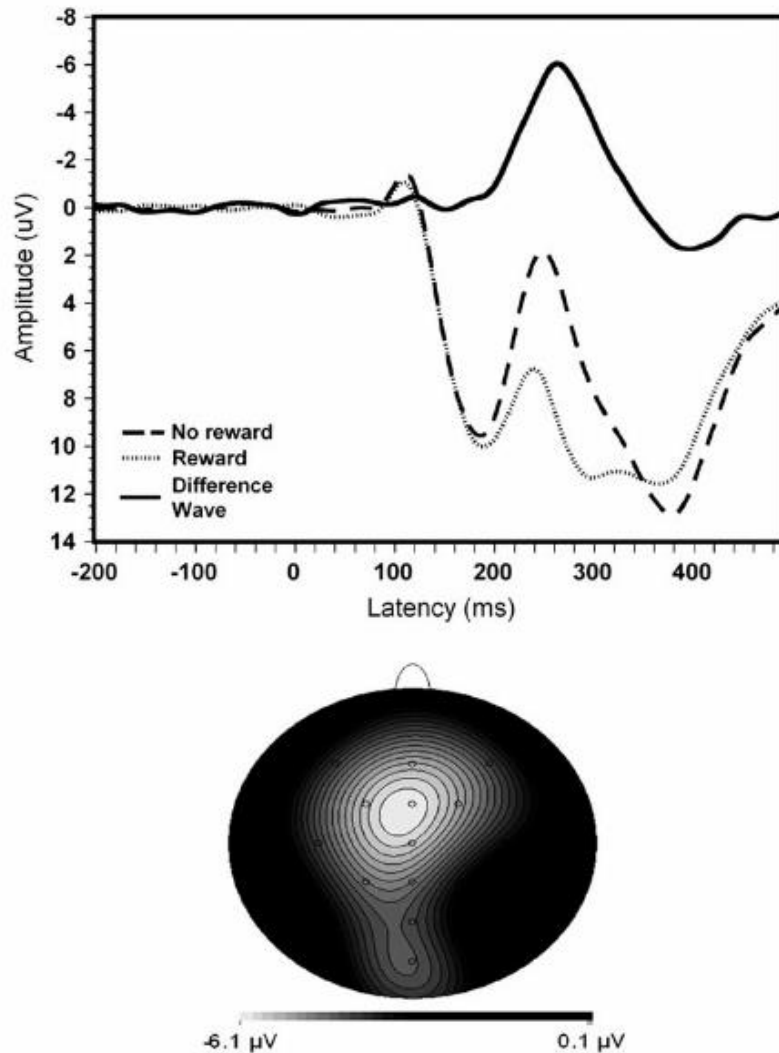


Figure 1. Example ERPs for reward/positive feedback and no-reward/negative feedback and the associated difference wave, which is characteristically observed approximately 250 ms following feedback. Also shown is a scalp voltage map demonstrating activity is maximal over front-central electrodes. Note that Negative is plotted up by convention. Adapted from Baker and Holroyd (2009).

The reward positivity was previously proposed to reflect the delivery of RPE signals to the ACC in order to allow the ACC to use these signals to modify behaviour in keeping with principals of the RL theory (Holroyd and Coles, 2002; Walsh and Anderson, 2012; Sambrook and Goslin, 2015). According to the HRL-ACC theory, the reward positivity uses these RPE signals to learn the value of the overall task, rather than concerning itself with trial-to-trial changes in behavior (Holroyd and Yeung, 2012; Holroyd and Umemoto, 2016). Evidence supporting this theory is demonstrated in the observation that reward positivity amplitude is sensitive to both contextual and state factors that influence motivation. For example, Threadgill and Gable (2016) found the amplitude of the reward positivity was enhanced in conditions in which approach-motivated pre-goal states were induced. The reward positivity has also been demonstrated to be sensitive to the overall task context in which rewards are delivered, over and above trial-to-trial learning (Umemoto, HajiHosseini, Yates, & Holroyd, 2017).

To summarize, the reward positivity is an electrophysiological measure of RPE signals carried by the MDS, which allow the ACC to learn the value of tasks and use these values to select tasks and motivate task-relevant behaviours. As addictive substances have been shown to stimulate the release of DA from the MDS (Chiara & Imperato, 1988), the reward positivity provides a useful tool to investigate changes in reward processing in individuals with SUDs. Based on the theory that substances of abuse cause exaggerated DA RPE signals, an ERP study used the reward positivity to test the hypothesis that disrupted RPE signals precipitate compulsive drug use (Baker, Stockwell, Barnes, & Holroyd, 2011). In this particular experiment, the reward positivity was generated with a pseudo-trial and error learning task in which participants navigated a “virtual T-maze” to find monetary rewards (Baker & Holroyd, 2009). A truncated reward positivity observed in undergraduate students reporting substance dependence was taken as evidence that individuals

with SUDs have impaired reward processing. A subsequent study demonstrated that genetically determined over-expression of the DA DRD4 receptor, which is highly expressed in the ACC and frontal cortex, can increase vulnerability to substance misuse by indirectly altering ACC response to feedback (Baker et al., 2016). Using the same virtual T-maze task, a follow-up study examined the reward positivity in response to monetary and cigarette rewards in a sample of cigarette smokers. A critical condition found that the reward positivity elicited by cigarette rewards was larger than the reward positivity elicited by monetary rewards, suggesting that in substance users, drug-related rewards engage the ACC more strongly than do non-drug related rewards (i.e., money) (Baker, Wood, & Holroyd, 2016; see also Baker et al., 2017).

A recent study examined ERP responses to positive and negative feedback in cocaine users. They found a decreased ERP response to negative feedback in cocaine users who had been abstinent for some time and those who had used cocaine in the previous 72 hours. The authors concluded there is an underlying impairment in DA driven learning (RPE signals) from negative or disadvantageous experiences in cocaine users (Parvaz et al., 2015, but see Baker & Holroyd, 2015). Another study found no relationship between reward positivity amplitude and alcohol use, but found that individuals reporting a history of alcohol problems in their family displayed a smaller reward positivity. This was interpreted to mean impaired reward processing is an inherited characteristic that increases vulnerability to substance use (Fein & Chang, 2008).

The impact of substance use on RPE signals has also been examined through fMRI. In response to positive feedback, cocaine dependent individuals were shown to have reduced sensitivity in DA-driven reward processing regions (Rose et al., 2014). Rose and colleagues (2012) also reported reduced RPEs in cigarette smokers, which appeared to be related to chronic nicotine use, as it was not impacted by acute nicotine. Reduced RPEs were also observed in polysubstance

users when compared to non-dependent individuals (Tanabe et al., 2013). Reduced discrimination between rewarding and non-rewarding events was also observed in opioid-dependent patients (Gradin, Baldacchino, Balfour, Matthews, & Steele, 2013). In contrast, Park and colleagues (2010) found no difference in RPEs in the striatum of alcohol-dependent individuals, but rather reported abnormal functional connectivity between the striatum and prefrontal cortex.

Complicating the picture is the finding that individual differences have been proven to impact proclivity to substance use and may mediate the relationship of SUDs and reward processing. For example, in addition to evidence for impaired DA-dependent reward processing in individuals with SUDs, Baker and colleagues (2011) also identified that individuals scoring high on a self-report measure of depression-proneness displayed disrupted error learning. Indeed, the magnitude of the reward positivity has been shown to be sensitive to a number of individual differences including depression (Proudfit, 2015; Umemoto & Holroyd, 2017), anhedonia (Liu et al., 2014; Parvaz et al., 2016), extraversion (Cooper, Duke, Pickering, & Smillie, 2014), impulsivity (Onoda, Abe, & Yamaguchi, 2010; Schmidt, Holroyd, Debener, & Hewig, 2017), and sensation seeking (Zheng & Liu, 2015). Many of these individual differences or personality traits are linked with increased risk for substance misuse, including impulsivity, sensation seeking, hopelessness, and anxiety sensitivity (Woicik, Stewart, Pihl, & Conrod, 2009).

Recently, the United States National Institute of Mental Health has promoted the Research Domain Criteria (RDoC) framework, which seeks to reconceptualise mental health disorders according to common underlying constructs rather than defining disorders based on their symptomatology. The RDoC model proposes that these underlying constructs, based on behavioural and neurobiological mechanisms, are expressed as a continuum. That is, expression of a construct on either end of the continuum is more likely to be associated with clinical

difficulties, while moderate expression of the same construct is more often associated with typical or healthy behaviours (Kozak & Cuthbert, 2016). Drawing from the RDoC framework and the HRL-ACC model, Holroyd and Umemoto (2016) recently proposed that if the ACC is responsible for motivating and selecting higher-order behaviours, then ACC function must also underlie individual differences in traits associated with the motivation of extended behaviours, such as persistence and reward sensitivity. In line with the RDoC framework, they proposed that extreme expression of these traits (i.e., persistence and reward sensitivity) would be associated with clinical disorders with a common underlying deficit in the motivation of extended behaviours. Holroyd and Umemoto argued that impaired ACC function is a critical component in a number of mental health disorders including substance use. That is, impaired ACC function is the common denominator across individual differences related to persistence and reward sensitivity (i.e., anhedonia and impulsivity). This is in line with the observations outlined above that the reward positivity, a neurological marker of ACC function, is impacted by various clinical disorders and individual differences.

The LPP has been used to investigate substance users' response to substance-related stimuli. A recent meta-analysis found evidence for an increased LPP in response to substance-related stimuli in users (Littel, Euser, Munafò, & Franken, 2012). For example, an increased LPP in response to cocaine-related stimuli in cocaine users was not present in a healthy control group (Dunning et al., 2011; Franken et al., 2008). Cigarette smokers had a larger LPP in response to cigarette pictures in comparison to a control group of never-smokers (Minnix et al., 2013). The LPP has also been used to predict the likeliness of cigarette smokers remaining abstinent from smoking. While all smokers displayed increased LPPs in response to cigarette stimuli, a group of smokers that also demonstrated a blunted LPP to intrinsically pleasant pictures were less likely to

successfully abstain from smoking in comparison to a group with a typical LPP to pleasant stimuli (Versace et al., 2012). The finding of a reduced LPP amplitude in response to non-substance related pleasant pictures in a subset of cigarette smokers was replicated in young smokers without a long history of substance use (Engelmann, Versace, Gewirtz, & Cinciripini, 2016), and in a group of current cocaine users (Dunning et al., 2011). Noteworthy is the finding that it was the LPP generated by non-substance related stimuli that predicted individual differences in current use and likeliness of remaining abstinent. This raises the question of whether reduced LPP to pleasant pictures is perhaps driven by underlying individual differences in affective instability. To the best of my knowledge, there are no studies to date examining the impact of individual differences in affect intensity, lability, and urgency on the LPP in either substance users or non-users.

Summary and Aims

Misuse of substances is a growing public health concern. SUDs are complex and the development and maintenance of SUDs are impacted by a number of factors including biological and psychological considerations. While the role of cognitive control has been well researched, the impact that affective processes have on substance use and reward processing is not as well understood. Individual responses to emotional situations and stimuli greatly vary. The overarching purpose of the current study was to investigate the relationships between substance use, affective instability, and neural mechanisms of reward and emotion processing.

Traditionally, affective instability – which refers, in part, to clinically significant difficulty with affect intensity, lability, and responsivity to environmental triggers -- has been examined in clinical populations, primarily BPD. Recently there has been a push to move from a categorical to a dimensional diagnostic system, as clinicians and researchers have begun to appreciate that psychological traits exist on a continuum from healthy to extreme. In line with this is the RDoC

framework which seeks to advance the understanding of underlying constructs that, when expressed on extreme ends of the continuum, contribute to psychological disorders (Kozak & Cuthbert, 2016). In order to advance the understanding of affective stability across the continuum of expression, the current study sought to examine components of affective instability in a non-clinical population. To the best of my knowledge, there have not been any studies to date that have used the AIM, ALS, and UPPS-P together to investigate the relationship between affect intensity, lability, and positive and negative urgency.

The first goal of the current study was to examine the relationship between the AIM, ALS, and positive and negative urgency subscales from the UPPS-P (see Table 1), as well as how these dimensions correlate with personality traits previously determined to increase risk for substance use (SURPS, Woicik et al., 2009). I was also interested in exploring the relationship between the questionnaires and self-reported substance use. Examining the relationship between these questionnaires will help to clarify the differences and similarities between the constructs they measure, as well as how they interact to increase risk of substance use.

Based on the observation that individual differences related to perseverance and reward sensitivity impact reward processing, as reflected in the reward positivity (Holroyd and Umemoto, 2016), the second goal of the current study was to determine whether individual differences in affective instability would be reflected in the amplitude of the reward positivity, and if this would differ depending on whether individuals reported high or low rates of substance use. To do this, I aimed to first replicate the finding of a truncated reward positivity, using a standard virtual T-Maze task (Baker, 2012; Baker et al., 2011, 2016), in a new sample of undergraduate students reporting high rates of substance use, and then to examine the impact of individual differences in affective instability on the effect. As the reward positivity is believed to be a neural correlate of the RPE

signal carried by the MDS to the ACC, it was used as an electrophysiological marker of reward processing. By examining the amplitude of the reward positivity, I was able to infer changes or disruptions in the underlying neural mechanisms of reward processing. As the role of affective instability in substance use is poorly understood, I was interested in determining whether the neural mechanisms of substance use would differ between high-risk substance users reporting high levels of affective instability and those reporting low affective instability.

Further, to investigate the impact of individual differences on emotion processing, I modified a task paradigm that was used previously in an fMRI study to show a functional link between task-independent emotional stimuli and an increased RPE signal in the striatum (Watanabe et al., 2013). Here, instead of using fMRI, I used the reward positivity to evaluate the impact of emotional stimuli on RPE signals. Notably, Watanabe and colleagues did not assess individual differences that may impact emotional processing. Thus, I first sought to replicate their observation of an increased RPE signal (as inferred from reward positivity amplitude) following presentation of emotional stimuli that were unrelated to the task, and then to investigate the impact of individual differences in affective instability on the amplitude of the reward positivity. To the best of my knowledge, no studies have examined the effect of individual differences in affective processing on electrophysiological measures of emotion processing. Therefore, I was interested in exploring whether individual differences in affective instability might also be reflected in the amplitudes of the P300 and LPP.

To achieve these goals, undergraduate participants completed two T-Maze tasks, one of which included emotional stimuli, while their ongoing EEG was recorded. For both tasks, the reward positivity was used as a measure of reward processing, while the P300 and LPP were used to evaluate emotion processing. Following the two tasks, participants completed a series of

questionnaires to assess current levels of substance use, subjective levels of affective instability, and personality traits associated with increased risk of substance use.

Several predictions follow from the above hypotheses. First, I predicted that individuals reporting higher levels of affective instability (i.e. affective lability, intensity, and urgency) would be more likely to report higher rates of substance use. Second, I predicted that I would replicate the results of previous studies, namely, that individuals reporting higher rates of substance use would display a truncated reward positivity in the Standard T-maze (Baker, 2012; Baker et al., 2011, 2017; Baker, Wood and Holroyd, 2016). Third, based on the results of Watanabe and colleagues (2013) -- who found an increased RPE signal following task-independent emotional stimuli -- I expected that the reward positivity amplitude in the Emotion T-maze would be larger following trials in which participants were presented with an emotionally salient picture. Fourth, as the reward positivity has been demonstrated to be sensitive to a number of individual differences (i.e., reward sensitivity), I predicted individuals reporting greater affective instability would be more sensitive to rewarding stimuli which would be evident in larger electrophysiological responses to reward feedback (as elicited by the Standard T-Maze task). Fifth, I expected the amplitude of the reward positivity following emotional stimuli (as elicited by the Emotion T-Maze task) to be even more exaggerated in individuals reporting high levels of affective instability. Putting these predictions together, I predicted that greater affective instability would 'normalize' reward positivity amplitude in risky substance users, which is otherwise truncated in this population. Specifically, I predicted reward positivity amplitude in individuals reporting both risky substance use and high affective instability would be larger than the amplitude of the reward positivity in those reporting risky substance use and low affective instability and that this effect would be particularly evident following emotionally valent pictures in the Emotion T-Maze task.

Finally, I predicted that individuals reporting high levels of affective instability would also have larger electrophysiological responses to emotion processing, as reflected in the amplitudes of the P300 and LPP.

Methods

Participants

Participants were students at the University of Victoria who received extra credit in an undergraduate psychology course for their participation. In order to participate, individuals were required to have normal or corrected-to-normal vision, no known history of neurological impairments and be fluent in English. In addition, all participants were given a performance-related monetary bonus of approximately CDN \$10 at the completion of the experiment (see below). All participants provided written informed consent.

Two previous studies with undergraduate student participants at the University of Victoria (Baker, 2012; Baker, Stockwell, Barnes, & Holroyd, 2011) found large effect sizes (Cohen's $d = 0.91$ and 0.87 , respectively) of substance use on the reward positivity. A power analysis using the average effect size (Cohen's $D = 0.89$) indicated a minimum of 68 participants were needed to achieve statistical power of 0.8.

A total of 84 undergraduate students participated in the experiment. Two participants over 40 years old were excluded from analysis as outliers in age. Data were analyzed for 50 females and 32 males ($n = 82$) between the ages of 18 – 28 years ($M = 21.30$, $SD = 2.47$). The experiment was approved by the human research ethics board at the University of Victoria and was conducted in accordance with the ethical standards prescribed in the 1964 Declaration of Helsinki.

Procedure

Participants completed a Standard T-Maze task, immediately followed by an Emotion T-Maze task while the EEG was recorded from electrodes placed on their scalp. After completing both tasks, the electrodes were removed and participants completed several questionnaires. Administration of the tasks and questionnaires all took place in private testing rooms in the ERP

laboratory. During data collection, participants were alone in the testing room and seated comfortably in front of a computer monitor. As part of the set up and consent process, all participants were informed of the presence of a video camera that allowed the experimenter to monitor the participant during the experiment.

Tasks.

Standard T-Maze. During the first task, participants navigated their way through a simple T-shaped “virtual maze” to find rewards. The T-maze task is a pseudo-trial and error learning task that has been demonstrated to elicit a robust reward positivity (Baker & Holroyd, 2009; Baker et al., 2011; Lukie, Montazer-Hojat, & Holroyd, 2014). Each trial began with an image of the stem alley of the T-maze, which remained on the screen for 1000 ms (see Figure 2). Subsequently, a green double arrow appeared at the end of the alley indicating that the participant could turn either left or right, and remained on the screen until the participant pressed a corresponding button on a keyboard (button 1 for left and button 2 for right). Following the choice, the image of the selected alley appeared on the screen for 500 ms, followed by an image of either an apple or an orange presented at central fixation over the alley (1000 ms). At the beginning of the task, participants were informed that one image (apple or orange) indicated that they had won 5 cents (reward feedback) and the other image was worth 0 cents (no-reward feedback). Reward stimuli were counterbalanced across participants. On each trial, the type of feedback stimulus was randomly selected, meaning there was a 50% probability of receiving reward or no-reward feedback, however participants were not informed of this contingency. Participants were told they would receive the total amount of money found in the maze at the end of the experiment and were encouraged to navigate the maze in a way that would maximize their earnings. The task was comprised of two blocks containing 50 trials each. Blocks were separated with a rest break, at

which time the experimenter checked on the participant and confirmed the amount of money accumulated so far. The duration of the rest break was controlled by the participant.

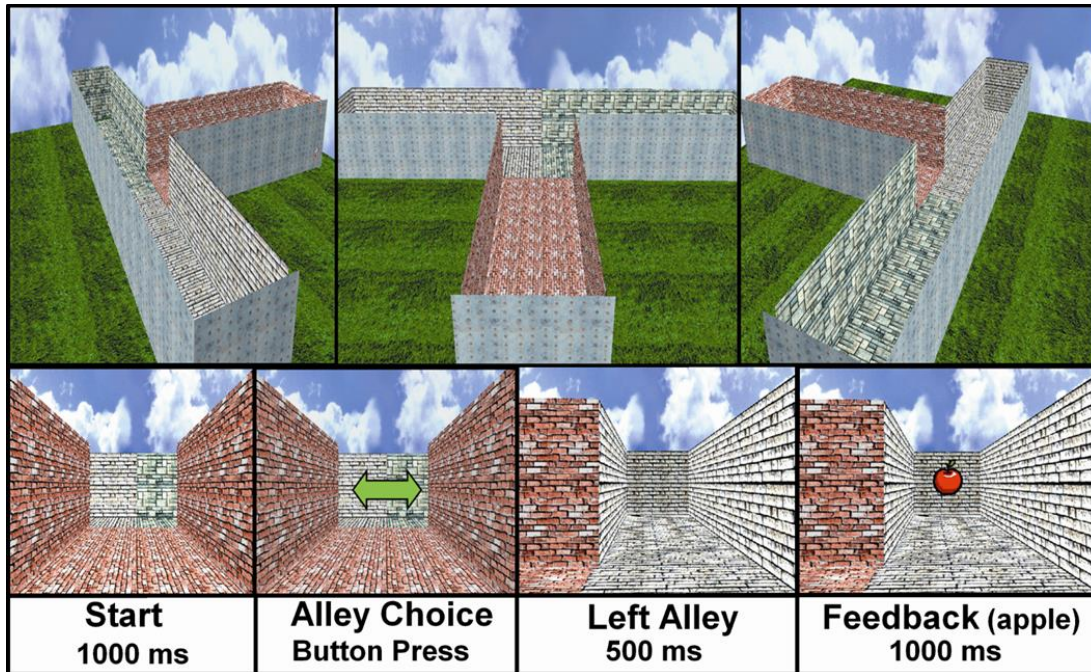


Figure 2. The Standard T-Maze task, a pseudo-trial and error learning task that elicits robust reward positivites. Images on the top depict the layout of the task, while the images on the bottom display the sequence of events during a single trial (adapted from Baker & Holroyd, 2009).

Emotion T-Maze. Following the Standard T-maze task, participants were given a similar task in which, prior to the appearance of the green double arrow on the screen, a picture from the International Affective Picture System (IAPS) (Lang, Bradley, & Cuthbert, 2008) was displayed at central fixation (overlaid on the alley image) for 1000 ms (see Figure 3). A total of 60 pictures comprising 20 neutral, 20 pleasant and 20 unpleasant images were selected. Pictures from the IAPS were selected based on the valence and arousal ratings included with the stimuli in the technical manual. In accordance with local ethics approval for the experiment, images with high arousal ratings containing erotica or mutilation were excluded from the sets. Participants were informed

of the nature of the images prior to beginning the experiment and were instructed to pay attention to the picture while it was on the screen. Immediately following the IAPS picture, the green double arrow appeared on the screen, indicating to participants they could select either the left or right alley. This image was followed by an image of the base alley for 500 ms, and then an image of the selected alley remained on the screen for 1000 ms. Next, feedback stimuli indicating whether or not they had found a reward (apple or orange) appeared on the screen for 1000 ms. Finally, the base alley appeared for 1000 ms and then the next trial began. Note that the mappings between feedback stimuli and reward types remained consistent for each participant across the two T-maze tasks.

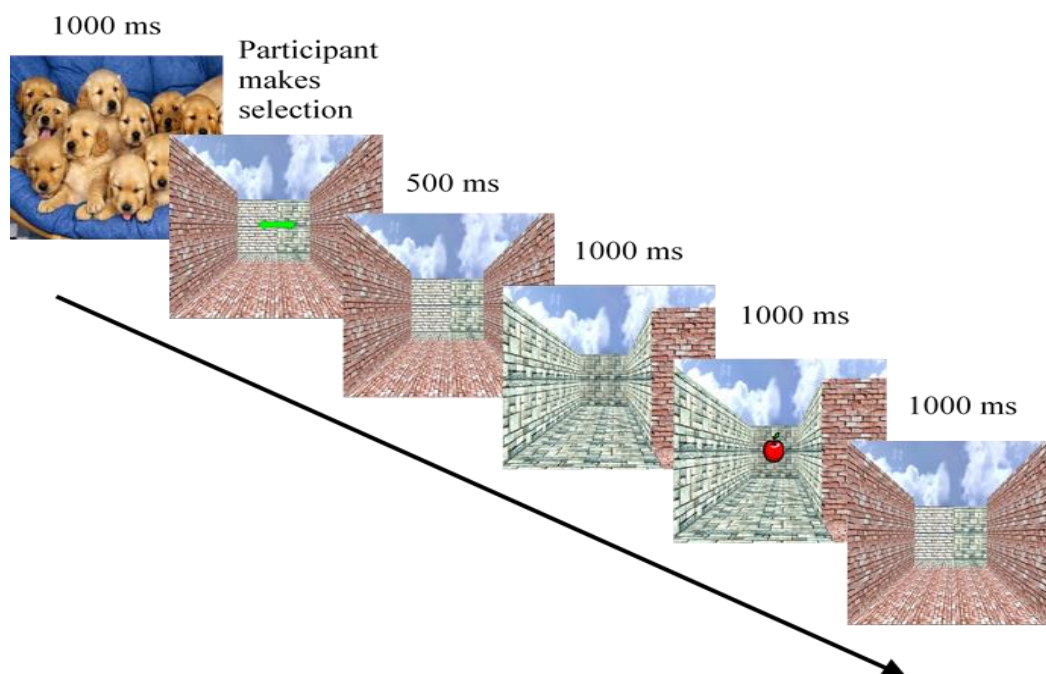


Figure 3. Sequence and timing of stimuli in the Emotion T-Maze task. Note the picture depicted is for illustrative purposes only and was not one of the pictures from the IAPS, nor was it used in the task.

Participants completed a total of five blocks consisting of 60 trials per block, for a total of 300 trials. During each block, participants were shown each of the 60 pictures one time. Pictures

were selected at random and were not linked with the subsequent reward or no-reward feedback, which occurred with equal (50%) probabilities. Participants were not told that the mappings were random and were encouraged to navigate the maze in a way that maximized their earnings. Between blocks, participants were provided with a self-controlled rest break, during which the experimenter summarized the participants' accumulated earnings. Note that at the end of the 300 trials, each participant had seen the 60 pictures five times each, resulting in 100 trials of each the neutral, pleasant and unpleasant picture conditions.

Questionnaires. After both tasks were completed, participants were asked to complete a computer-based survey comprised of five questionnaires. Each participant completed the survey privately in the ERP lab testing room and all questionnaire data were anonymized by use of a participant number. On average, participants took between 15 and 20 minutes to complete the computerized survey.

First, participants completed the Alcohol, Smoking and Substance Involvement Screening Test V3.0 (ASSIST V3.0) (Humenuik, Henry-Edwards, Ali, & Poznyak, 2010; Humenuik et al., 2008), which was used in previous reward positivity studies of substance dependence (Baker et al., 2011; Baker, Stockwell, & Holroyd, 2013). The ASSIST is a screening test designed by the World Health Organization (WHO) to detect substance use and related difficulties in primary medical care settings. Specifically, the ASSIST screens use of tobacco, alcohol, cannabis, cocaine, amphetamines, inhalants, sedative, hallucinogens, opioids and "other drugs", providing a robust measure of polysubstance use. The ASSIST assesses a variety of factors related to substance dependence, including frequency of substance use in the past three months, cravings, negative consequences as a result of substance use, and evidence of loss of control. The ASSIST only requires participants to answer questions pertaining to substances they reported using and uses a

weighted scoring system to generate substance-specific risk scores. Recommended cut off scores for 'low risk' is ≤ 3 for all substances except alcohol, which has a cut off ≤ 10 , 'moderate risk' scores include the range of 4-26 or 11-26 for alcohol, any substance specific score ≥ 27 is considered 'high risk' (Humenuik et al., 2008). Additionally, an 'overall substance use' score was calculated by summing the substance specific scores; in previous studies (Baker, 2012; Baker et al., 2011, 2017; Baker, Wood, & Holroyd, 2016) this was referred to as the Global Continuum of Risk score (GCR). For the current study, the ASSIST V3.0 was modified from paper to a computerized format.

Three additional questionnaires assessed aspects of affective instability. These consisted of a short form of the Affective Lability Scale – 18 (ALS-18) (Look et al., 2010; Oliver & Simons, 2004), the Affect Intensity Measure (AIM) (Larsen & Diener, 1987) and the UPPS-P Impulsive Behavior Scale (UPPS-P) (Cyders et al., 2007; Whiteside et al., 2005).

The ALS-18 was originally developed as a 56-item measure for use with a non-clinical population (Harvey, Greenberg, & Serper, 1989). Participants respond using a four-point Likert scale, the purpose of the measure is to identify patterns of instability in affect or the frequency and intensity of changes in affect. The original measure has been shown to have good internal consistency, test-retest reliability and discriminant validity (Harvey et al., 1989). More recently the ALS was modified to a shorter version comprised of 18 items from the original measure (Oliver & Simons, 2004). The ALS-18 correlates strongly with the original ALS, with high internal consistency and good test-retest reliability. Exploratory and confirmatory factor analysis determined that a three-factor model of anxiety/depression, depression/elation and anger best fit the short form version of the ALS. Subsequent studies that have sought to verify the psychometric

properties of the ALS-18 with clinical populations have confirmed good convergent validity, strong construct validity and high internal consistency (Aas et al., 2015; Look et al., 2010).

The AIM is a 40-item questionnaire that measures the magnitude or intensity with which an individual experiences his or her emotions (Larsen & Diener, 1987). Affect intensity is conceptualized as a trait characteristic or individual difference and the AIM is focused on the intensity, rather than frequency of emotions. The AIM has good psychometric properties including strong test-retest reliability, internal consistency, and discriminant and convergent validity (Bagozzi & Moore, 2011; 1995; Larsen & Diener, 1987). Factor analyses of the AIM indicated that it describes four correlated factors – positive affectivity, negative reactivity, negative intensity and positive intensity (Rubin, Hoyle, & Leary, 2011; Weinfurt, Bryant, & Yarnold, 1994).

The UPPS-P was selected specifically for two subscales related to positive and negative urgency. Positive and negative urgency relate to individual differences in propensity for impulsive actions or responses driven by the experience of either positive or negative emotions, respectively. The original measure, UPPS Impulsive Behavior Scale, consisted of 45 items selected to create four factors of impulsivity – negative urgency, lack of premeditation, lack of perseverance and sensation seeking (Whiteside & Lynam, 2001). The UPPS was demonstrated to have good internal consistency and construct validity, and could adequately discriminate between healthy individuals and those with psychopathology (Whiteside et al., 2005). A fifth factor, positive urgency, was added through the addition of 14 items, resulting in the UPPS-P (Cyders et al., 2007). The five factor UPPS-P has good internal consistency, test-retest reliability, and content validity (Cyders et al., 2007; Whiteside et al., 2005).

The last questionnaire was the Substance Use Risk Profile Scale (SURPS) (Woicik, Stewart, Pihl, & Conrod, 2009). The SURPS is a 23-item measure of four personality traits –

hopelessness, sensation seeking, anxiety sensitivity and impulsivity – that have been shown to be related to substance use. It has good psychometric properties including concurrent and predictive validity as well as good sensitivity and specificity (Castellanos-Ryan, O’Leary, Sully, & Conrod, 2013). The SURPS was included in the current study to replicate the methods of previous reward positivity studies involving substance dependent individuals (Baker, 2012; Baker et al., 2011).

The subscales/factors from the individual differences questionnaires (AIM, ALS-18, SURPS and UPPS-P) have previously been demonstrated to measure unique components of affective processing (Cyders & Smith, 2007; Look, Flory, Harvey, & Siever, 2010; Oliver & Simons, 2004; Rubin, Hoyle, & Leary, 2011; Weinfurt, Bryant, & Yarnold, 1994; Woicik, Stewart, Pihl, & Conrod, 2009). To this effect, data from the questionnaires were initially examined according to the three factors from the ALS-18, four AIM factors, positive and negative urgency, and the four personality traits identified by the SURPS for a total of 13 subscales. In order to reduce the data and explore the relationships between the questionnaires, relationships between the 13 subscales were explored to determine whether the data was suitable for a Principal Components Analysis (PCA). Finally, in order to examine the effect of individual differences on ERP components, participants were classified as ‘high’ and ‘low’ according to quartile scores for each of the factors determined by the PCA.

Data Acquisition and Analysis

The electroencephalogram (EEG) was recorded from 41 electrode sites using BrainVision Recorder Software (Brainproducts, GmbH, Munich, Germany). The electrodes were mounted in a fitted nylon cap with a standard 10-20 layout and were referenced to a common ground. For the purpose of artifact correction, the horizontal electrooculogram (EOG) was recorded from the external canthi of both eyes. The vertical EOG was recorded from the suborbit of the right eye and

electrode channel Fp2. Inter-electrode impedances were kept below $20\text{k}\Omega$ and two electrodes were placed on the right and left mastoids. The EEG data were sampled at a rate of 250 Hz and were amplified by low-noise electrode differential amplifiers with a frequency response of dc 0.017-67.5 Hz (90dB octave roll off).

Post processing was performed using Brain Vision Analyzer software (Brain Products, GmbH). The EEG data were filtered through a phase-shift-free Butterworth filter with a passband of 0.10-20 Hz. For the Standard and Emotion T-maze tasks, an 800 ms epoch of data extending from 200 ms prior to feedback stimulus onset to 600 ms following the stimulus was extracted from the continuous EEG for analysis. In addition, for the Emotion T-Maze task a 1200 ms epoch of data extending from 200 ms prior to IAPS picture onset to 1000 ms following picture onset, corresponding to the time of picture offset, was also extracted for analysis. Ocular artifacts were corrected using the eye movement correction algorithm described by Gratton, Coles, and Donchin (1983). The epochs were re-referenced to the average value recorded at the mastoid electrodes and baseline corrected by subtracting from each sample the average activity recorded at that electrode during the 200 ms interval preceding stimulus onset. Muscular and other artifacts were removed using a $\pm 150\mu\text{V}$ level and $\pm 35\mu\text{V}$ step threshold rejection criteria. The Hjorth nearest-neighbor correction was applied to excessively noisy data for individual channels.

To assess the neural response to reward and no-reward stimuli, ERPs were created for each electrode and participant by averaging the single-trial EEG according to feedback type (reward or no-reward) for both the Standard and Emotion T-maze tasks. For the Emotion T-maze task, reward and no reward ERPs were separately created for the neutral, pleasant and unpleasant conditions. The reward positivity was measured at electrode site FCz, where it typically reaches maximum amplitude (Walsh & Anderson, 2012). For each participant, the average ERP waveform elicited

by reward feedback was subtracted from that of the corresponding no-reward feedback to create a difference wave (Holroyd & Coles, 2002; Miltner, Braun, & Coles, 1997). Reward positivity amplitude was measured as the mean activity of the difference wave within a 270-300 ms window post-stimulus, as recommended in a meta-analysis by Sambrook and Goslin (2015). Reward positivity latency was defined as the time when the difference wave was most negative at channel FCz within a 200-400 ms window following feedback onset. To examine the effect of emotional pictures on the RPE, I compared the amplitude of the reward positivity to feedback following the presentation of emotionally valent pictures vs. the presentation of emotionally neutral pictures.

For the Emotion T-maze task, data corresponding to the presentation of IAPS pictures were averaged for each participant and channel separately for neutral, pleasant, and unpleasant pictures. The P300 was measured as the mean activity at channel Pz within a 300-500 ms window, where it typically reaches maximum amplitude (Donchin & Coles, 1988). LPP was measured as the mean activity at channel Pz and examined throughout different time windows as previously advised (Hajcak et al., 2012; Hajcak, MacNamara, & Olvet, 2010). The window from 500-1000 ms comprised the entire LPP complex. Activities from 500-750 ms and from 750-1000 ms were conceptualized as “early LPP” and “late LPP”, respectively. In addition, the entire positivity comprising the P300 and LPP was measured as mean activity at Pz from 300-1000 ms.

Data were statistically analyzed with SPSS v 15.0. In instances in which the assumption of sphericity was violated (according to Mauchly’s sphericity test), a Greenhouse-Geisser correction was used to reduce Type 1 error.

Results

Questionnaires

Data were analyzed for 82 participants. Substance specific scores and an overall substance use score were calculated from responses to questions on the ASSIST v3.0. Thirty-six participants were classified as “low risk”, as they reported minimal substance use; the remaining 46 “risky use” participants reported a minimum of moderate risk use for at least one substance. Of those 46 reporting at least moderate risk, 27 reported moderate or high risk for more than one substance (polysubstance use)¹. There were no individuals who reported high risk use of a specific substance and did not also report at least moderate risk use of a second substance, therefore these individuals were classified as at risk for polysubstance use. Independent t-tests did not find any significant differences between males and females in regard to overall substance use or specific substance use (all p s > .05).

Data from the individual differences questionnaires were initially examined according to the subscales comprising each of the questionnaires. Preliminary analysis demonstrated that 12 of the 13 subscales correlated at least .3 with one other subscale. Factorability was further examined by observing the Kaiser-Meyer-Olkin measure of sampling adequacy of .754, above the commonly recommended value of .6 (Tabachnick & Fidell, 2007), and Bartlett’s test of sphericity was significant ($\chi^2 (78) = 456.85, p < .001$). In addition, the diagonals of the anti-image correlation matrix were all over .5 and the communalities were all above .3, confirming that each subscale shared some common variance with other subscales. Given these overall indicators, PCA was used

¹ Data were also analyzed using an overall substance use score or GCR score (see Baker et al., 2011); the results did not differ from the results reported above and were not statistically significant.

to identify and compute composite scores for common factors underlying the questionnaire subscales.

Initial eigenvalues indicated that the first four factors, which all had eigenvalues greater than 1.0, explained 36%, 16%, 10% and 8% of the total variance, respectively. The remaining factors all had eigenvalues less than one. Following varimax rotation, the resulting four factor solution explained 70% of the variance (Table 2). Inspection of the factor loadings revealed the following observations. First, the four subscales from the SURPS loaded mostly separately across the four factors. Second, subscales assessing affect intensity loaded according to valence (i.e., positive and negative intensity loaded onto different factors) and separately from lability and urgency. This was somewhat surprising because intensity and lability, which have traditionally been considered key dimensions of affective instability, were separated here into two separate factors, and further, because lability was grouped together with urgency, which has not been widely considered within the affective instability literature. Third, the impulsivity and hopelessness scales from the SURPS also loaded onto the lability/urgency factor. I therefore named this factor “reactivity” to reflect increased responsivity to affective stimuli as assessed by lability and urgency subscales, and to distinguish it from affective instability, which by definition includes other affective components such as affect intensity. Fourth, four subscales relating to anxiety and negative emotionality loaded onto Factor 2, which I labelled “neuroticism”. Last, in accordance with the remaining SURPS loadings around which they grouped, Factors 3 and 4 were labelled “positivity” and “sensation seeking”, respectively. As the reactivity factor encompassed most of the subscales relating to affective instability (aside from the affect intensity subscales), this factor was used to represent affective instability in the subsequent analyses. A series of independent t-tests were run to investigate gender differences amongst the four factors. Females

reported significantly greater levels of neuroticism ($t(80) = 2.26, p < .05, \eta_p^2 = .06$); no other comparisons were significant ($ps > .05$).

	<i>Reactivity</i>	<i>Neuroticism</i>	<i>Positivity</i>	<i>Sensation Seeking</i>
<i>UPPS-P Negative Urgency</i>	0.858			
<i>SURPS - Impulsivity</i>	0.771			
<i>UPPS-P Positive Urgency</i>	0.734			
<i>ALS-18 - Anxiety/Depression</i>	0.673	0.488		
<i>ALS-18 - Depression/Elation</i>	0.659			
<i>AIM - Negative Intensity</i>	0.654	0.407		
<i>ALS-18 - Anger</i>	0.624			-0.47
<i>AIM - Negative Reactivity</i>		0.895		
<i>SURPS - Anxiety Sensitivity</i>		0.789		
<i>AIM - Positive Affectivity</i>			0.819	
<i>SURPS - Hopelessness</i>	0.519		-0.682	
<i>AIM - Positive Intensity</i>			0.678	
<i>SURPS - Sensation Seeking</i>				0.904
Total Eigenvalue	4.64	2.04	1.35	1.08
% of Variance	35.7	15.7	10.3	8.3
Cumulative % of Variance	35.7	51.4	61.8	70

Table 2. Factor loadings and communalities based on a principal components analysis with varimax rotation for 13 subscales from the AIM, ALS-18, SURPS and UPPS-P ($n = 82$), and factor loadings for 4-factor PCA solution.

Note: Factor loadings $< .4$ are suppressed.

Correlation and multiple regression analyses were conducted to examine the relationship between overall substance use and the four identified factors. A multiple regression model with all four factors as predictors indicated that the four factors were correlated with substance use, $R^2 = .220, F(4,77) = 5.431, p < .01$. Table 3 summarizes the correlation and regression results. As can be seen, reactivity and sensation seeking positively correlated with overall substance use, indicating those with higher scores on these factors tend to report higher rates of substance use. Reactivity and sensation seeking had significant positive regression weights, indicating individuals

high on these factors are expected to report higher substance use after controlling for the other predictors in the model. Further, reactivity contributed more strongly than sensation seeking to the regression. Neuroticism and positivity did not contribute to the multiple regression model. As an exploratory analysis, I investigated the relationships between the four factors and specific substances, the results of which are reported in Appendix A.

	<i>Reactivity</i>	<i>Neuroticism</i>	<i>Positivity</i>	<i>Sensation Seeking</i>
<i>Correlation</i>	0.409***	-0.034	-0.072	.215*
<i>B</i>	8.146***	-0.673	-1.431	4.269*

Table 3. Correlations of 4 PCA factors with Overall Substance Use score and unstandardized regression coefficients (B).

Note: standardized regression coefficients (β) were not reported as the factors were previously standardized, thus the standardized regression coefficient is reflected in the correlation coefficient. * $p < .05$, *** $p < .001$

ERP Results

Figure 4 illustrates the ERPs elicited by the Reward and No-Reward feedback during the Standard and Emotion T-Mazes and associated difference waves, averaged across participants separately for the Low Risk and Risky Use groups. The ERPs for both groups revealed a typical reward positivity maximal at channel FCz to both the Standard T-Maze (Low Risk: $M = -4.29 \mu V$, $SE = .50 \mu V$; Risky Use: $M = -3.72 \mu V$, $SE = .61 \mu V$) and Emotion T-Maze (Low Risk: $M = -4.61 \mu V$, $SE = .50 \mu V$; Risky Use: $M = -4.13 \mu V$, $SE = .49 \mu V$). Contrary to my prediction, a repeated measures ANOVA on reward positivity amplitude with maze condition (standard, emotion) as a within-subject factor and Low Risk and Risky Use as a between-subject factor revealed no effect of maze conditions, group, or interaction (all $ps > .05$) (Figure 5).



Figure 4. Event-related brain potentials (ERPs) time-locked to the onset of reward/no reward feedback (at 0 ms) measured at FCz (negative is plotted up by convention). Difference waves (blue solid line) were calculated by subtracting the reward ERPs (red dotted line) from the no-reward ERPs (yellow dashed line). **A:** ERPs elicited by the Standard T-Maze for individuals reporting low substance use ($n = 36$). **B:** ERPs elicited by the Emotion T-Maze for individuals reporting low substance use. **C:** ERPs elicited by the Standard T-Maze for individuals reporting high substance use ($n = 46$). **D:** ERPs elicited by the Emotion T-Maze for individuals reporting high substance use.

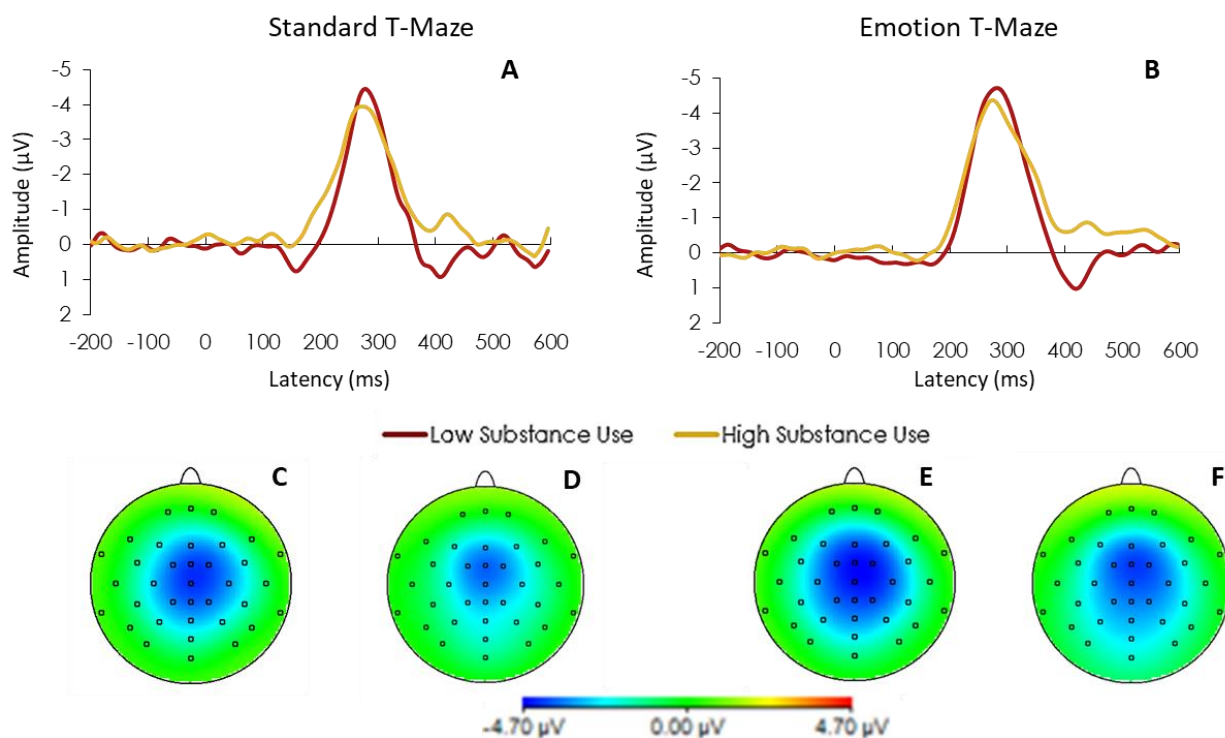


Figure 5. Difference Waves and associated scalp voltage maps. Difference waves were calculated by subtracting the reward ERPs from the no-reward ERPs at channel FCz and are time-locked to the onset of feedback (at 0ms). Scalp distributions were averaged from 270 – 300 ms, the time in which reward positivity amplitude was measured. **A:** Difference waves for low (red) and high (yellow) substance users elicited by the Standard T-Maze task. **B:** Difference waves for low and high substance users elicited by the Emotion T-Maze task. **C:** Scalp distribution of low substance users in the Standard T Maze. **D:** Scalp distribution high substance users in the Standard T Maze. **E:** Scalp distribution of low substance users in the Emotion T Maze. **F:** Scalp distribution of high substance users in the Emotion T Maze.

To test the prediction that a larger reward positivity would be elicited following the presentation of an emotional picture, I used a repeated measures ANOVA with valence (neutral, pleasant, unpleasant) entered as within-subject factors. There were no significant effects of valence on the reward positivity (all p s > .05).

To test whether affective reactivity had an effect on the amplitude of the reward positivity, participants were split into groups based on top and bottom quartiles according to their score on

the reactivity factor. A repeated measures ANOVA on reward positivity amplitude with maze condition (standard, emotion) as a within-subject factor and low ($n = 21$) and high ($n = 20$) reactivity as a between-subject factor revealed no effect of maze condition, group, or interaction (all p s $> .05$). But based on my prediction that individuals scoring high on affective instability would have a greater response to emotional pictures, which in turn would increase the subsequent reward positivity, I compared reward positivity amplitude across groups separately for trials in which participants were shown an emotionally valent picture. Reward positivity amplitude was larger following emotionally valent pictures for highly reactive ($M = -5.46 \mu\text{V}$, $SE = .68 \mu\text{V}$, Figure 6c) compared to minimally reactive ($M = -3.46 \mu\text{V}$, $SE = .67 \mu\text{V}$, Figure 6a) individuals ($t(39) = 2.103$, $p < .05$, $\eta_p^2 = .10$ Figure 7a and c). In contrast, there was no significant difference in reward positivity amplitude on neutral picture trials between highly ($M = -4.37 \mu\text{V}$, $SE = .74 \mu\text{V}$) and minimally ($M = -3.48 \mu\text{V}$, $SE = .66 \mu\text{V}$) reactive individuals ($t(39) = .903$, $p > .05$, (Figures 6b, 6d and 7c). As an exploratory analysis, differences in the amplitude of the reward positivity between groups scoring high or low on the remaining factors (neuroticism, positivity, and sensation seeking) were also examined. No significant differences in reward positivity amplitude were observed for any of the other factors across either the Standard or Emotion T-mazes.

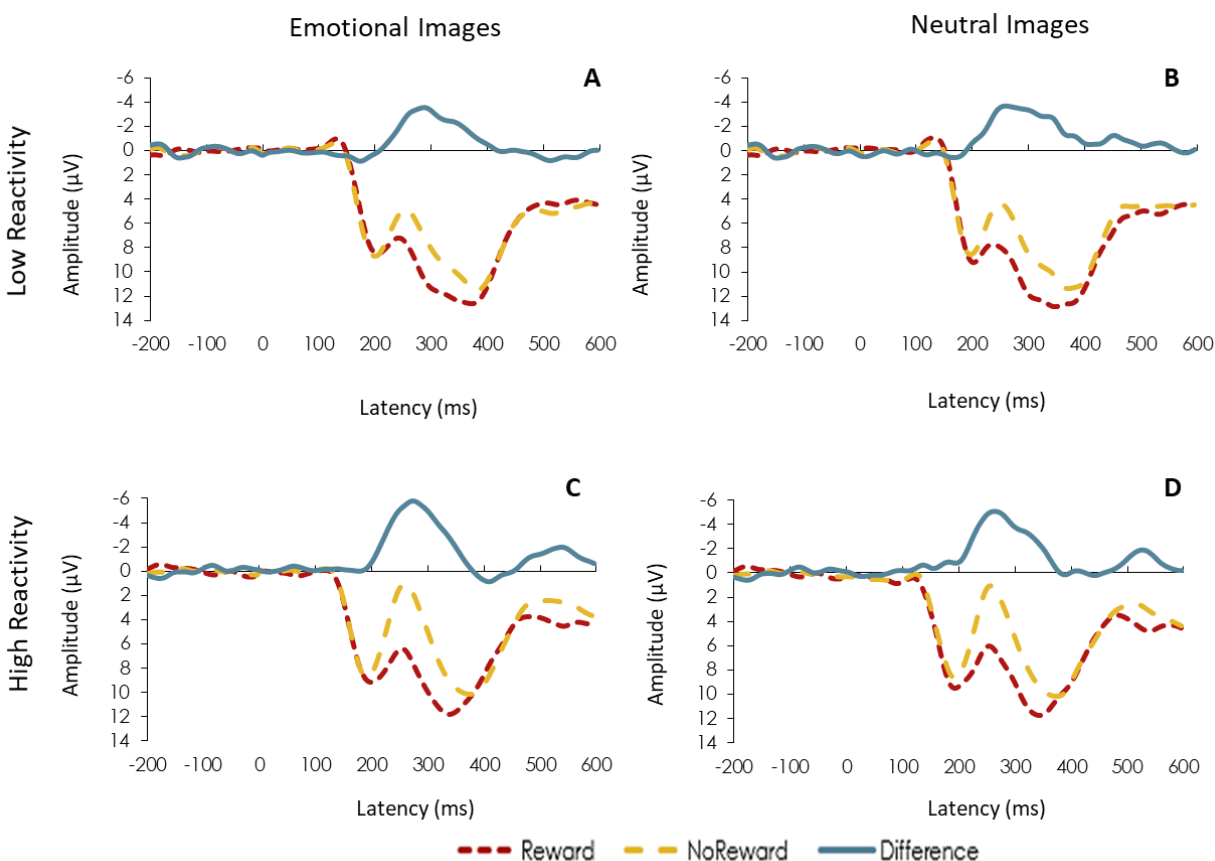


Figure 6. Event-related brain potentials (ERPs) time-locked to the onset of reward/no reward feedback (at 0ms) measured at FCz (negative is plotted up by convention). Difference waves (blue solid line) were calculated by subtracting the reward ERPs (red dotted line) from the no-reward ERPs (yellow dashed line). **A:** ERPs elicited by feedback stimuli following emotionally valent pictures for individuals reporting low reactivity ($n = 21$). **B:** ERPs elicited by feedback stimuli following neutral pictures for individuals reporting low reactivity **C:** ERPs elicited by feedback stimuli following emotionally valent pictures for individuals reporting high reactivity ($n = 20$). **D:** ERPs elicited by feedback stimuli following neutral pictures for individuals reporting high reactivity.

To test the prediction that reward positivity amplitude would be larger in risky substance users who score high versus low on affective reactivity, participants scoring high on substance use were categorized according to their affective reactivity scores. Of the 46 participants reporting risky substance use, 14 scored in the top quartile for affective reactivity and eight scored in the bottom quartile. The amplitude of the reward positivity on trials with emotionally valent pictures

was larger for individuals reporting high affective reactivity ($M = -5.53 \mu\text{V}$, $SE = .87 \mu\text{V}$) compared to individuals reporting low affective reactivity ($M = -2.16 \mu\text{V}$, $SE = 1.21 \mu\text{V}$) ($t(20) = -2.30$, $p < .05$, $\eta_p^2 = .21$) (Figure 8). In comparison, no difference in the amplitude of the reward positivity was found between the groups following neutral pictures ($t(20) = -.763$, $p > .05$). As an exploratory analysis, the same independent t-tests were run on reward positivity amplitude to the feedback following emotional stimuli in the emotion task, for low risk substance users reporting either high ($n=6$) or low ($n=13$) affective reactivity. There were no significant differences in reward positivity amplitude between groups (all p s $> .05$).

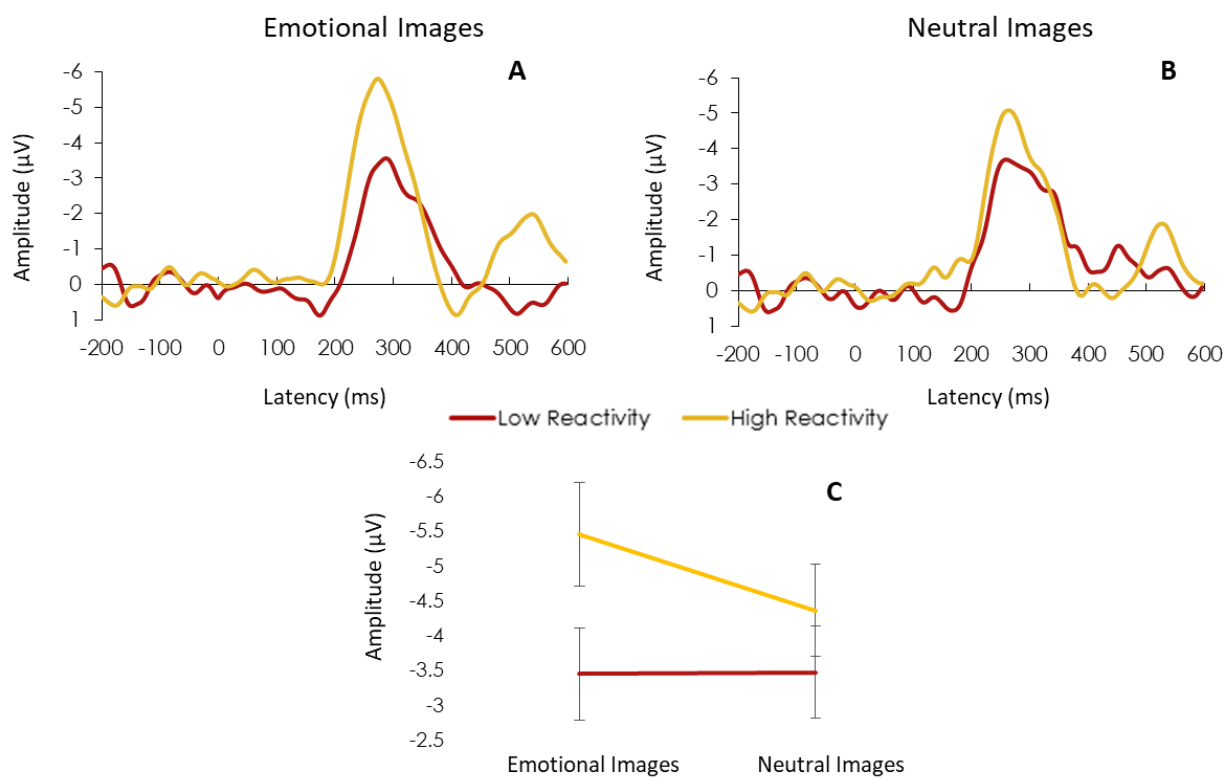


Figure 7. Difference Waves following reward feedback for individuals reporting low (red) and high (yellow) affective reactivity following emotional valent (A) and neutral (B) IAPS images on the Emotion T-Maze task. C: Difference in reward positivity amplitude for low and high affective reactivity following emotional and neutral IAPS images. Error bars represent Standard Error. Note: Negative is plotted up by convention.

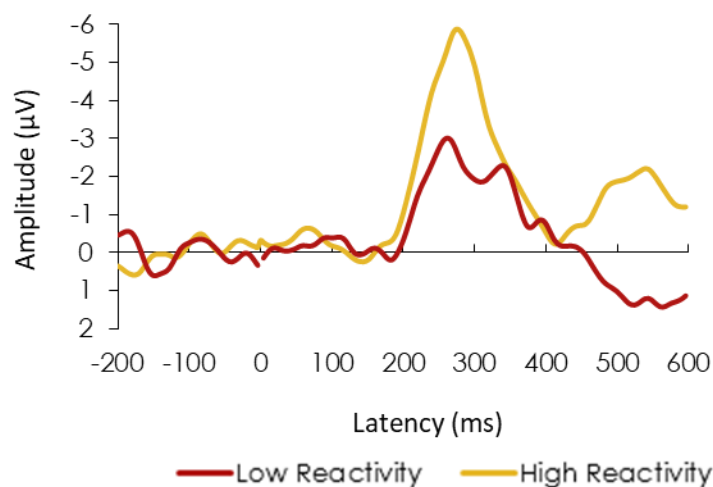


Figure 8. Difference Waves following reward feedback for high substance users reporting low (red, $n = 8$) and high (yellow, $n = 14$) affective reactivity following emotionally valent images on the Emotion T-Maze task.

Differences in the positive deflection following presentation of the IAPS pictures were initially examined with a two-way repeated measure ANOVA with time (P3, 300-500 ms; early LPP, 500-750 ms; late LPP, 750-1000 ms) and valence (neutral, pleasant, unpleasant) entered as within-subject factors (Figure 9). Main effects for time ($F(1.34, 108.8) = 59.8, p < .001, \eta_p^2 = .43$) and valence ($F(1.84, 148.91) = 145.3, p < .001, \eta_p^2 = .64$), and the interaction between time and valence ($3.16, 255.89 = 42.5, p < .001, \eta_p^2 = .34$) were all significant. In order to elucidate the effect of valence on the mean activity of the positive deflection in each of the time windows, three separate repeated measure ANOVAs for each of the time windows (300-500 ms, 500-750 ms, and 750-1000 ms) with valence as the within-subject factor (neutral, pleasant, unpleasant) indicated significant differences for all three conditions (all $ps < .05$). A series of post hoc analysis with a Bonferroni adjustment revealed that mean activity was initially largest for pleasant pictures in the time window of the P300 (300-500 ms), but after 500 ms, mean activity was larger following unpleasant pictures (Table 4). As mean activity was largest following unpleasant pictures in both

time windows of the early and late LPP, for the remainder of analyses, the LPP was measured as mean activity in the 500-1000 ms window.

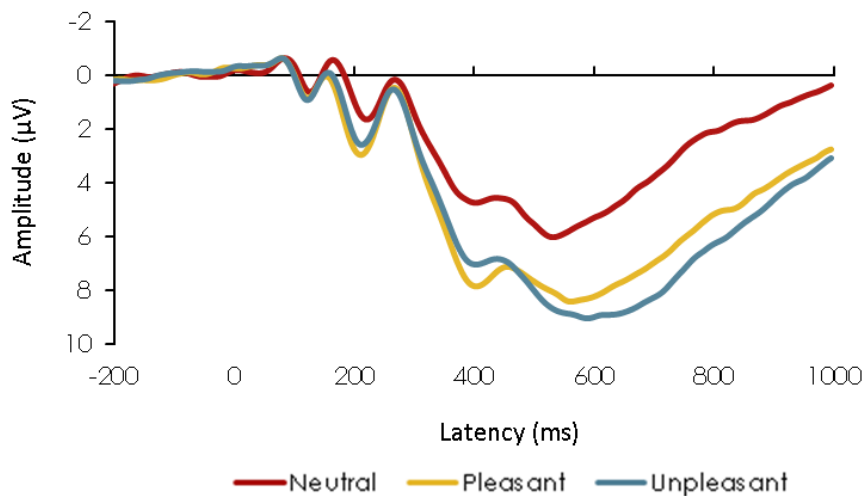


Figure 9. Event-related brain potentials (ERPs) time-locked to the onset of IAPS picture stimuli (stimulus onset at 0 ms) measured at channel Pz (negative is plotted up by convention).

	<i>P300 (300-500 ms)</i>	<i>Early LPP (500-750 ms)</i>	<i>Late LPP (750-1000 ms)</i>
<i>Neutral</i>	4.07 (.44)***	4.8 (.33)***	1.47 (.25)***
<i>Pleasant</i>	6.41 (.45)*	7.63 (.36)***	4.32 (.27)***
<i>Unpleasant</i>	6.02 (.48)*	8.55 (.38)***	5.10 (.30)***

Table 4. Mean voltage and standard errors (μV) at Pz across three different time windows following presentation of neutral, pleasant, and unpleasant pictures from the IAPS.

P300: ***Mean voltage in the neutral condition differed significantly ($p < .001$) from the pleasant and unpleasant conditions.

*Mean voltage in the pleasant condition was also significantly greater ($p < .05$) than in the unpleasant condition.

Early and Late LPP: ***Mean voltage in all three conditions differed significantly ($p < .001$) from each other.

I predicted that individuals reporting high affective instability would have a larger neural response to emotional pictures. In order to investigate the impact of affective reactivity on the mean activity of the P300 and LPP, a 3-way mixed-design repeated measures ANOVA on ERP

amplitude with affective reactivity as a between-subject factor and valence (neutral, pleasant, unpleasant) and time window (P300 and LPP) as within-subject factors revealed no significant effects between reactivity, valence, and time (all p s > .05). As an exploratory analysis, the same ANOVA was run with high and low risk substance use entered as the between-subject factor; similarly, none of the effects were significant.

Finally, on trials with emotionally valent stimuli for highly reactive individuals, an exploratory analysis failed to find statistically significant correlations between reward positivity amplitude with either P300 amplitude or LPP amplitude. The same analyses conducted across all subjects also failed to reveal any statistically significant relationships (all p s > .05).

Discussion

The current study sought to investigate the relationship between substance use, affective instability, and reward and emotion processing. Substance use is a growing problem and clinicians and researchers continue to search for a better understanding in order to inform more effective treatments. The fact that impaired emotional processing influences the development and maintenance of SUDs is well established (Cheetham, Allen, Yücel, & Lubman, 2010) but the specific role of affective instability has received less attention. A key barrier includes the lack of consistency in defining and assessing affective instability. The current study sought to first investigate the relationship between affect intensity, lability, and urgency, key dimensions in affective instability, and next to examine how individual differences in these affective dimensions influence substance use and neural mechanisms of reward and emotion processing.

Dimensions of Affective Instability in a Non-Clinical Sample

Recent research has suggested that the construct of affective instability is multi-faceted and that the construct should be assessed using multiple questionnaires. The ALS and AIM, which respectively measure traits of affective lability and intensity, have been specifically recommended for this purpose (Marwaha et al., 2014; Renaud & Zacchia, 2012). In addition to lability and intensity, I was also interested in investigating how positive and negative urgency might relate to affective instability. While urgency has not traditionally been considered a dimension of affective instability, as it characterizes the responsiveness of an individual to their emotions, it appears to be a closely related concept. Until recently, affective instability has been defined and understood in the context of clinical disorders in which it is a primary symptom (i.e. BPD). The current study sought to understand the relationship between different dimensions of affective instability within a non-

clinical population. To do this, I administered to undergraduate students the AIM, ALS, and the positive and negative urgency scales from the UPPS, as well as the SURPS, which measures personality traits that predict substance dependence. An exploratory PCA on the subscales from all of the questionnaires identified four factors that mostly loaded separately across the four personality dimensions measured by the SURPS. Additionally, subscales from the AIM loaded separately according to valence (i.e., positive and negative affect), and separately from a factor associated with the ALS and urgency subscales. Results indicated that affect lability, urgency, and impulsivity were strongly related to each other. Specifically, the factor on which impulsivity (SURPS) loaded most strongly also involved positive and negative urgency, all of the subscales from the ALS (anxiety/depression, depression/elation, and anger), negative intensity (AIM), and hopelessness (SURPS). I named this factor “reactivity” (or affective reactivity) as the subscales largely measured how individuals respond to their emotions, as well as how quickly and easily their emotions change. In comparison to the remaining factors identified by the PCA, the reactivity factor is most closely related to affective instability, but differs in that it excludes affect intensity and includes positive and negative urgency.

The other factors were named based on the personality dimensions from SURPS that loaded separately across the remaining factors. The second factor, neuroticism, included anxiety sensitivity (SURPS), negative reactivity and intensity (AIM), and lability between negative emotions (anxiety/depression). The third factor, positivity, included positive affectivity and intensity (AIM), and a negative relationship with hopelessness (SURPS). The fourth factor, sensation seeking (SURPS), also included a negative relationship with anger (ALS). Overall, the reactivity factor encompassed active changes (lability) or behaviours (urgency) in response to emotions. The remaining factors pertained to affect intensity, which loaded separately by valence

(i.e., negative emotions loaded on the neuroticism factor, while positive emotions loaded on the positivity factor). Finally, sensation seeking was pulled out as a separate factor mostly unrelated to subscales measuring affective dimensions. These results speak to a clear distinction between the intensity with which individuals experience their emotion and how reactive or ‘unstable’ their emotions are.

A lack of a concise, established definition of affective instability has recently come under criticism (Marwaha et al., 2014; Renaud & Zacchia, 2012). Two proposed definitions of affective instability suggest that affect intensity is a key component; however, the current results indicate that, in a non-clinical population, affect intensity loads separately from both lability and urgency. This suggests affect intensity represents a unique dimension of affective processing and should be considered as a separate concept in the conceptualization and measurement of affective instability. This distinction may not be clear when examining dimensions of affective instability in clinical populations. For instance, Kuo and Linehan (2009) proposed that affect intensity, not lability, is responsible for emotional dysregulation observed in individuals with BPD. Whereas Renaud and Zacchia (2012) observed mixed results regarding affect intensity in individuals with BPD and postulated that this may be explained by high rates of comorbid PTSD, thereby dampening responses to emotional stimuli. By better understanding the differences between affect intensity and reactivity, it might aid in furthering our understanding of how these processes might separately impact the presentation of emotional dysregulation observed across clinical disorders. Koenigsberg (2010) hypothesized that there may be two subtypes of affective instability, each associated with different psychological or personality disorders. As affect intensity has traditionally been considered together with reactive dimensions of affective instability, it is unclear if conceptualizing intensity as a separate trait would change our understanding of how affective

instability presents in clinical populations. For example, the relationship between lability and intensity may be quite different across disorders, while they may both significantly contribute to affective instability in BPD, intensity may contribute less or differently to affective instability observed in PTSD. The fact that affective instability has been primarily researched in clinical populations potentially complicates the understanding of underlying dimensions as other symptoms or difficulties associated with a given disorder may impact the expression of different dimensions of affective instability. The current results help to elucidate the makeup of affective instability in a non-clinical population.

Affective Instability and Substance Use

The results of the PCA allowed me to elucidate how different dimensions of affective instability (i.e. lability and urgency) contribute to increased risk of substance use. Of the four factors identified by the PCA, only reactivity and sensation seeking predicted increased overall substance use, with the correlation between affective reactivity and substance use being nearly twice as large as that between sensation seeking and substance use. The importance of this relationship is bolstered by the finding that reactivity was a stronger predictor of substance use than all four personality dimensions assessed by the SURPS (see Appendix A), a questionnaire designed to measure personality traits associated with increased risk for substance abuse (Woicik et al., 2009). To date, only a handful of studies have looked at the relationship between affective lability and intensity and substance use. Typically, research has focused on the relationship between these affective dimensions and specific substances or populations and results have not always been straight-forward (Coskunpinar, Dir, & Cyders, 2013; Fischer & Smith, 2008; Lagerberg et al., 2017; Rankin & Maggs, 2006; Simons et al., 2005). A recent study sought to elucidate the potential roles of negative affect, affective lability, and negative urgency on

problematic alcohol use (Coskunpinar et al., 2013). Coskunpinar and colleagues concluded that negative affect (defined as neuroticism) and increased lability act to increase negative urgency, which in turn predicted problematic alcohol consumption; however, the mechanism by which negative urgency increases alcohol use remains poorly understood. One hypothesis is that individuals high in negative urgency experience strong emotions that deplete resources related to cognitive control and decision making (Cyders & Smith, 2008). My results contradict this hypothesis as affect intensity loaded separately both from lability and urgency, and did not significantly predict substance use.

My results suggest that affective reactivity is an important trait that should be addressed when assessing and treating individuals with SUDs. In comparison, affect intensity did not predict substance use. The reactivity factor encompasses increased emotional and behavioural responses to emotional stimuli and can be considered an ‘active’ dimension of affective instability. As such, individuals high on reactivity are more inclined to act on emotional changes or distress by behaving (i.e. consuming a substance) in such a way as to distract from, or add to (in the case of positive urgency), their emotional experience. By contrast, affect intensity is a more passive dimension, the degree to which an individual feels their emotions is an internal experience and does not necessarily equate to outward behaviour. Disassembling the components of affective processing may help to clarify why previous studies have reported inconsistent results regarding the impact of different affective processes on substance use across various populations. A better understanding of the relationship between components of affective instability may help guide future research to more effective treatment and prevention methods.

Substance Use and Reward Processing

After exploring the relationships between components of affective instability and substance use, I was interested in determining the impact of affective instability and substance use on neural mechanisms of reward and emotion processing. Toward this end, I had a number of predictions regarding the impact that affective instability and substance use would have on the reward positivity, P300, and LPP, some of which were supported, while others were not. First, I predicted that I would replicate a truncated reward positivity in individuals reporting problematic substance use (Baker, 2012; Baker et al., 2011, 2016, 2017). In a series of studies, Baker and colleagues used the ASSIST v3.0 to assess substance use, and the Standard T-Maze task to elicit the reward positivity. They found evidence of impaired reward processing demonstrated through a truncated reward positivity in a sample of undergraduate students reporting substance dependence (Baker et al., 2011). Baker argued that the smaller amplitude of the reward positivity in substance users reflected desensitization to non-drug rewards like the nominal financial gains used in the task. This hypothesis was supported by a later study that found that substance dependent smokers displayed a larger reward positivity to cigarette rewards in comparison to monetary rewards (Baker et al., 2017; Baker et al., 2016). Although the current study used the same methodology as Baker and colleagues with a new sample of undergraduate students, I did not replicate their finding of smaller reward positivity amplitude for individuals reporting high-risk substance use compared to individuals reporting minimal substance use.

Several possibilities could account for this failure to replicate the finding of a smaller reward positivity in high-risk substance users. The current study quantified substance use based on specific substance scores (as suggested by the WHO), whereas Baker used quartile scores that roughly corresponded to previously recommended cut-offs for substance dependence (GCR >

39.5) (Newcombe et al., 2005). However, this difference did not impact the current results as when I ran the analyses using the overall substance use score/GCR score, as done in the previous studies, the results remained unchanged. The key difference between the current study and those reported by Baker and colleagues (2011, 2016, 2017) appears to be the degree of substance use reported by the different samples. The overall substance use score for the top quartile in the current sample was 26.25, substantially lower than rates of substance use reported in previous studies that found a truncated reward positivity (>39.5) (Baker, 2012; Baker et al., 2011, 2016). Based on effect sizes from previous studies (Baker, 2012; Baker et al., 2011), it was determined that a minimum of 68 participants was required to have enough power to replicate the finding. Yet despite the current study exceeding this number, participants reported lower rates of substance use, limiting the ability of the current study to replicate previous findings. It should also be noted that even results with strong effect sizes will not always be replicated due to factors such as distribution of effect sizes and sampling error (Schimmack, 2012). Even with power set at 80%, there is a 20% chance that a real statistical effect will not be replicated. Thus, the current results may be an example of expected non-replication.

Emotional Stimuli and Reward Processing

I also predicted that I would observe an increased RPE signal to feedback following the presentation of task-independent emotional stimuli, as previously found in an fMRI study by Watanabe and colleagues (2013), but failed to do so. Several reasons might account for this. First, the current study utilized the reward positivity as a measure of the RPE signal, whereas Watanabe and colleagues assessed the strength of the RPE signal in the ventral striatum by examining the BOLD signal. It is important to note that the effect size of this result was not reported by Watanabe and colleagues, however it was noted that the effect was only significant when the threshold was

set at $p < .05$. It is possible the effect of emotional stimuli on the RPE signal is too small to be evident in the reward positivity. Further, I adapted the task used by Watanabe and colleagues in a number of ways as appropriate for use in an ERP study. Key differences between the two versions of the task, which are elaborated below, included the behavioural/learning task, timing of presentation of stimuli, and the type of emotional stimuli used.

The Emotion T-Maze task used in the current study was a modified version of the Standard T-Maze task, which has been used in a number of ERP studies to successfully elicit the reward positivity (Baker & Holroyd, 2009; Baker et al., 2011; Lukie, Montazer-Hojat, & Holroyd, 2014). It is based on a pseudo trial-and-error learning task in which the probability of receiving rewarding feedback is 50%, unbeknownst to participants. Participants were encouraged to respond in a manner so as to maximize reward feedback by selecting the alley that they believed the reward was in. By contrast, the task used by Watanabe and colleagues was a probabilistic learning task that participants were exposed to prior to the neuroimaging session. Despite differences between the tasks, both allowed for the production of RPE signals based on participants' predictions. A second difference between the tasks concerned the stimulus timing, which differed in order to accommodate the relative timings of the electrophysiological and hemodynamic responses. Namely, unlike the study by Watanabe and colleagues (2013), participants in the Emotion T-Maze controlled the duration of the alley fixation period following presentation the IAPS stimuli by pressing a button. Further, the reward outcomes were displayed for 500 ms less in the Emotion T-maze than in the fMRI task. Nevertheless, it seems unlikely these changes had an impact on the results, as both methods successfully elicited a RPE signal.

Finally, the Emotion T-Maze used pictures selected from the IAPS, where Watanabe and colleagues used fearful or neutral faces. The majority of ERP studies investigating emotional

processing have used IAPS stimuli (see Hajcak, MacNamara and Olvet, 2010 for review), as subjective arousal ratings for IAPS stimuli have been found to be more arousing in comparison to affective facial expressions (Britton, Taylor, Sudheimer, & Liberzon, 2006). Facial affective expressions are believed to require networks involved in emotion recognition, while IAPS pictures predominantly involve emotional evocation. Despite these differences, Britton and colleagues (2006) provided evidence that both pictures depicting emotional scenes (IAPS) and human faces displaying emotional expressions activate similar neural networks (amygdala, hippocampus, ventral medial prefrontal cortex, and visual cortex). However, processing of faces is a complex process that involves an initial stage of encoding, followed by processing of identity, changeable aspects of a face, and emotional expression all of which activate specific brain regions in addition to those in common with the IAPS (Britton et al., 2006; also see Palermo & Rhodes, 2007 for review). Faces and facial expressions also hold special social significance; for example, the LPP is enhanced in response to the presence of people and faces in otherwise neutral pictures (Ferri, Weinberg, & Hajcak, 2012; Weinberg & Hajcak, 2010). As I was interested in the impact of individual differences in affective instability, I chose to use pictures from the IAPS instead of facial expressions to mitigate the impact of individual differences in sensitivity to social stimuli and interactions. However, stronger amygdala response to affective facial expressions in comparison to scenes depicting emotionally stimulating content have also been reported (Hariri, Tessitore, Mattay, Fera, & Weinberger, 2002). It is possible that the current study's use of IAPS stimuli rather than emotional faces led to the lack of replication of an increased RPE signal following emotional stimuli. Yet conflicting with this possibility is the fact that the IAPS pictures successfully elicited larger LPPs in response to pleasant and unpleasant pictures in comparison to neutral pictures. As the LPP is believed to represent activation of an extensive neural network,

including cortical and subcortical structures, the modulation of the amplitude of the LPP by IAPS pictures increases the likelihood the pictures were processed by similar structures as were activated by emotional facial expressions in Watanabe and colleagues' study.

Affective Instability and Emotion Processing

As expected, LPP amplitude was larger following emotionally valent pictures in comparison to neutral pictures. However, in contrast to my prediction that I would observe larger electrophysiological responses to emotion processing in individuals reporting high levels of affective instability, I did not find any significant differences in the amplitude of the P300 or LPP between individuals reporting high versus low levels of reactivity. This is somewhat surprising as the LPP has been demonstrated to be sensitive to other individual differences in personality. For instance, Weinberg, Perlman, Kotov, and Hajcak (2016) found that individuals who reported an early onset of MDD showed reduced LPP amplitude in response to rewarding and threatening IAPS images. These findings are in line with previous studies that demonstrated a reduced LPP to threatening stimuli in individuals both diagnosed with (Foti & Hajcak, 2010) and at risk for depression (Kujawa, Hajcak, Torpey, Kim, & Klein, 2012). In a sample of adolescent females, self and informant-reported traits of extraversion were positively associated with increased LPP amplitude, whereas there was no effect of neuroticism on the LPP (Speed et al., 2015). Reduced LPP amplitude in response to aversive stimuli has also been observed in individuals with Parkinson's Disease who report high levels of apathy (Dietz et al., 2013). The impact of individual differences in anxiety on the LPP is less clear. Some studies report anxious individuals have larger LPP amplitudes in response to threatening stimuli (MacNamara & Hajcak, 2009, 2010), whereas others have found less differentiation between unpleasant and neutral pictures (Weinberg &

Hajcak, 2011), and others report anxiety symptoms do not impact the amplitude of the LPP (Weinberg et al., 2016).

In terms of individual differences relating specifically to affective instability, there have been few studies to date, and those that exist have been within the context of BPD. One study found that individuals with BPD had a larger LPP in response to unpleasant IAPS pictures in comparison to a control group (Marissen, Meuleman, & Franken, 2010). Another looked at the LPP in response to positive and negative words in young women with BPD and found an enhanced LPP to negative words (Auerbach et al., 2016). These results suggest abnormal emotional processing in individuals with BPD. Additionally, abnormal emotional processing in individuals with BPD displaying traits of affective instability have been further supported through fMRI findings of increased activations in the amygdala and insula when viewing aversive stimuli (Schulze et al., 2011). Koenigsberg, Siever, Lee, and Pizzarello (2009) also reported different activation patterns between individuals with BPD and controls in response to both unpleasant and pleasant stimuli. Although the measures used in the current study (ALS, AIM, UPPS) have not been used together in previous studies, a recent fMRI study involving women with BPD found affective lability, as assessed by the ALS, positivity correlated with greater amygdala activity (Silvers et al., 2016).

Results from fMRI and ERP studies with individuals with BPD suggest there is a relationship between the neural networks responsible for processing emotional stimuli and producing the LPP and BPD, of which affective instability is a primary symptom. As the current study examined affective instability in a non-clinical sample, it is likely that differences between groups represented mild differences, rather than the extreme expression of individual differences in affective processing seen in clinical disorders. To the best of my knowledge, this is the first

study that has examined the impact that non-clinical individual differences in affective instability have on neural processing of emotional stimuli. It may be that these subtler individual differences are not strong enough to elicit neurological changes in processing of emotional stimuli and therefore no differences in the amplitude of the LPP were observed based on self-reported levels of reactivity. Interestingly, a recent study examining mindfulness, a trait associated with lower levels of affective instability, also did not find an impact of self-reported trait mindfulness on the amplitude of the LPP (Cosme & Wiens, 2015).

The IAPS images used in the current study may be another possible factor in why I did not observe a difference in LPP amplitude between individuals reporting high and low levels of affective reactivity. Although the IAPS images used in the current study produced the expected effect on LPP amplitude (larger for emotionally valent pictures, see Table 4), they may have not been arousing enough to detect individual differences in emotional processing. The LPP has been demonstrated to be sensitive to more intense and arousing stimuli, such as erotica and threatening scenes (see Hajcak, MacNamara, & Olvet, 2010 for review). Due to ethical concerns, the current study did not use images involving erotica, threat, or violence.

One influential theory regarding the functional significance of the LPP is that it reflects increased visual attention that facilitates efficient processing of emotional information (Brown et al., 2012; also see Hajcak et al., 2010, 2012 for review). Based on this theory, it is possible that individuals reporting higher levels of affective reactivity purposely did not attend to emotionally evocative pictures due to the fact that they were more likely to have an emotional response. The LPP amplitude to unpleasant pictures has been demonstrated to decrease when participants are instructed to attend to less arousing aspects of the picture (Dunning & Hajcak, 2009; Hajcak et al., 2009). It is plausible that individuals who are more responsive to their emotions, in the context of

a psychology experiment, may have regulated their emotional response by decreasing their attention to the pictures overall or to the more emotionally stimulating aspects of the pictures. If this were the case, any potential impact of reactivity on the LPP amplitude may have been masked by unsolicited emotional regulation strategies. Alternatively, the LPP may not be sensitive to individual differences in reactivity. As the LPP is believed to be generated by an extensive brain network including subcortical and cortical structures (Liu, Huang, McGinnis-Deweese, Keil, & Ding, 2012), it is difficult to draw any firm conclusions regarding why it may or may not be sensitive to various individual differences.

Affective Instability and Reward Processing

Despite some of my predictions being disconfirmed, other fundamental predictions were supported. I predicted that individuals reporting higher levels of affective instability would be more sensitive to feedback and therefore produce a larger reward positivity. Further, I predicted that the reward positivity following emotional pictures on the Emotion T-Maze would be even larger than those elicited by the Standard T-Maze. As discussed above, a PCA identified a principal factor of affective reactivity, which encompassed active dimensions related to affective instability (i.e., lability and urgency). As this factor was most closely related to affective instability and demonstrated a significant relationship with substance use (as per my prediction regarding affective instability), I used scores on this factor to examine the impact of affective reactivity on neural mechanisms of reward and emotion processing. In fact, individuals reporting greater levels of reactivity only displayed a larger reward positivity following emotionally valent pictures. In comparison, the amplitude of the reward positivity elicited by the Standard T-Maze and following neutral pictures on the Emotion T-Maze did not differ between individuals reporting high and low reactivity (see Figures 6 and 7).

The RPE signal is believed to be generated by phasic DA changes in response to outcomes that are better or worse than expected, which is the premise behind reinforcement learning. Emotional stimuli hold evolutionary importance and are automatically processed faster than non-emotional stimuli (Brosch, Pourtois, & Sander, 2010). Watanabe and colleagues (2013) found a psycho-physiologic interaction between activation of the amygdala in response to fearful faces, and increased RPE signal in the striatum following fearful (in comparison to neutral) faces. This was interpreted as evidence of a system in which using facial expressions may evolutionarily have helped an individual to navigate their environment more efficiently and ultimately obtain more rewards. The results from the current study partially replicated the observation of an increased RPE signal following emotional stimuli; however, the amplitude of the reward positivity was only increased for individuals reporting higher levels of reactivity. Those participants who reported increased responsivity to their emotions showed a larger reward positivity following emotionally valent pictures. Building on the hypothesis of Watanabe and colleagues, these results suggest that individuals who are more reactive to emotional stimuli may activate neurological networks related to emotional processing more strongly, which in turn would enhance RPE signals in order to facilitate learning. Conflicting with this hypothesis is a lack of evidence for increased emotional processing, in individuals reporting higher levels of reactivity, as measured by the amplitude of the LPP. Additionally, the amplitude of the LPP did not significantly correlate with the amplitude of the reward positivity. However, as previously discussed, it is unclear precisely what the LPP is measuring and the relationship between self-reported affective reactivity and neural measures of emotion processing remains uncertain.

The effect of emotional stimuli on neural RPE signals is not well established. In addition to Watanabe and colleagues' finding that task-independent emotional stimuli appeared to increase

the RPE signal, another fMRI study used emotional pictures as decision outcomes and concluded that the emotional stimuli produced a prediction error that drove learning (Katahira et al., 2015). Two recent ERP studies examined the relationship between state and trait affect. One study found no main effect of trait positive or negative affect on the size of the feedback related negativity (FRN, i.e., the negative deflection in the ERP) to negative feedback, but did find an interaction between state and trait emotions and FRN amplitude (Riepl, Mussel, Osinsky, & Hewig, 2016). Specifically, Riepl and colleagues found that individuals reporting high trait negative affect produced larger FRNs following an anger induction, but not following fear or happiness inductions. The second ERP study reported smaller reward positivity amplitudes in neutral and fearful conditions in individuals reporting high trait anxiety in comparison to those reporting low trait anxiety, but only in response to smaller magnitude outcomes (Wang, Gu, Luo, & Zhou, 2017). The difference in reward positivity amplitude was not observed in happy conditions. Wang and colleagues hypothesized that individual differences in anxiety led to an expectation bias that was diminished in positive emotional conditions. The relationship between state and trait affective processes and reward processing appears to be complicated, with some evidence that the interaction between state and trait affect impacts neural mechanisms of reward processing. The results of the current study partially support previous ERP studies in that only those individuals reporting high trait affective reactivity showed a larger reward positivity following emotionally valent pictures (state affect).

These findings add to a growing literature regarding the sensitivity of the reward positivity in response to individual differences in personality. As it is well established that the reward positivity reflects reward processing (i.e. reward prediction errors) (Sambrook & Goslin, 2015), it is not surprising that it is sensitive to a number of individual differences related to reward

sensitivity (Holroyd & Umemoto, 2016; Proudfit, 2015). Factors related to reward sensitivity include reward responsiveness (i.e., the ‘liking’ of rewards), and approach motivation (i.e., ‘wanting’ of rewards) (Baskin-Sommers & Foti, 2015). Individual differences may be visible in the amplitude of the reward positivity in a number of personality traits and clinical symptoms related to reward sensitivity (see Holroyd and Umemoto, 2016 for review). Smillie, Cooper, and Pickering (2011) found a larger reward positivity in individuals reporting higher levels of extraversion in comparison to those individuals who identified as being introverted. They concluded that extraversion, characterized by behavioural approach and agency, is a putatively DA-based trait that was reflected in the increased reward positivity, demonstrating the sensitivity of the reward processing system to individual differences in personality. In 2014, Cooper, Duke, Pickering, and Smillie replicated and expanded on the observation that extraverted individuals displayed a larger reward positivity. Specifically, they explored the impact of extraversion, impulsivity, and reward sensitivity/anhedonia, traits considered to be constructs of the behavioural activation/approach system, as well as individual differences in anticipatory and consummatory pleasure. Individuals reporting higher levels of extraversion and anticipatory pleasure had larger reward positivities, whereas other individual differences such as impulsivity, reward sensitivity, and consummatory pleasure did not impact the amplitude of the reward positivity. This was taken as evidence that personality traits related to behavioural approach (extraversion) and anticipatory positive affect (anticipatory pleasure) are partially based in variation in the dopaminergic system. Additional studies have found a larger reward positivity in individuals reporting greater responsiveness or sensitivity to rewards (i.e. agency, drive, and anticipatory excitement) (Bress & Hajcak, 2013; Umemoto & Holroyd, 2017).

This may also be in line with research that has found a smaller reward positivity in individuals reporting symptoms of depression (see Proudfit, 2015 for review). This has been observed in non-clinical samples of undergraduate students reporting depressive symptoms (Foti & Hajcak, 2009; Umemoto & Holroyd, 2017), as well as in individuals diagnosed with major depressive disorder (MDD) (Liu et al., 2014). Proudfit (2015) proposed that a blunted reward positivity may act as a biomarker, or neural indicator of reduced reward sensitivity. At the crux of the relationship between depression and impaired reward processing is anhedonia, or the inability to experience pleasant events as pleasurable. Liu and colleagues (2014) found reduced amplitude of the reward positivity was related to increased symptoms of anhedonia in both individuals with MDD and a control group. Further, Foti and colleagues (2014) found the reduced reward positivity in individuals with MDD was driven by a lack of reactivity in response to positive events.

Understood in this context, it might be expected that individuals who are more responsive to emotional stimuli (i.e. those high on affective reactivity) would also be more sensitive to rewards and therefore would be expected to demonstrate the opposite pattern as that observed in individuals reporting high levels of anhedonia. Rewards are defined by their pleasure or hedonic impact (Berridge & Robinson, 1998). The reactivity factor in the current study assessed responsivity to emotional stimuli, which may be considered a facet of reward sensitivity if rewards are conceptualized as positive emotional experiences. Based on previous findings of the reward positivity being sensitive to individual differences in reward sensitivity, it is therefore not surprising that the amplitude of the reward positivity was observed to be larger in individuals reporting greater affective reactivity.

Interestingly, a larger reward positivity in individuals with higher levels of reactivity was only observed following emotionally salient pictures, which supported my prediction of increased

reward processing following emotional stimuli in individuals who are more reactive to affective stimuli. This may suggest that these individuals were stimulated by the emotional pictures and in turn paid closer attention and/or were more engaged in the task. There is mounting evidence that the reward positivity is sensitive to the degree to which participants are engaged in the task (Sambrook & Goslin, 2015). For example, Yeung, Holroyd, and Cohen (2005) found that the amplitude of the reward positivity was larger during tasks in which participants actively chose a response compared to passively observing the feedback, and also when they reported greater involvement in the task. Similarly, Martin and Potts (2011) found a reduced reward positivity on a passive choice task in which a computer, rather than participants, made selections. This was attributed in part to “boredom” or lack of engagement of participants on passive (as opposed to active) tasks. The reward positivity is larger when participants believe they are responsible for the resulting outcome or feedback (Bismark, Hajcak, Whitworth, & Allen, 2013; Li, Han, Lei, Holroyd, & Li, 2011), and larger when participants believed they were gambling for themselves in comparison to gambling for others (Krigolson, Hassall, & Handy, 2013). The amplitude of the reward positivity has also been shown to decrease when feedback is delayed (Peterburs, Kobza, & Bellebaum, 2016; Weinberg et al., 2012). The longer individuals were required to wait for feedback, the smaller the amplitude of the reward positivity, perhaps due to a decrease in task engagement and overall attention to the task. The finding that the reward positivity was larger for individuals reporting higher levels of affective reactivity only after emotionally salient pictures may speak to the pictures activating or motivating individuals to be more engaged in the task and more invested in the reward outcomes.

Affective Instability, Substance Use, and Reward Processing

A primary goal of the current study was to examine the impact of individual differences in affective instability on substance use and reward processing. Although I did not find a truncated reward positivity in high risk substance users, the reward positivity following emotionally valent stimuli was larger for high risk substance users reporting high levels of reactivity than those reporting low levels of reactivity. This supports my prediction that high levels of affective reactivity would ‘normalize’ an otherwise truncated reward positivity in high risk substance users. This observation of a larger reward positivity in high risk substance users reporting high levels of affective reactivity, considered alongside previous observations of a truncated reward positivity in substance dependent individuals, provides evidence of multiple paths to addiction (Baker, 2012). There are many biological and psychological traits that may predispose or increase risk of misuse of substances and the interaction of these traits may be difficult to decipher due to their potentially additive or counteracting effects. On the one hand, the previously observed truncated reward positivity is evidence that individuals with SUDs exhibit impaired reward processing, particularly in relation to naturally occurring (as opposed to drug-related) rewards (Baker et al., 2011; Baker, Wood & Holroyd, 2016). On the other hand, the results of the current study indicate that individuals reporting higher levels of affective reactivity are more likely to report risky use of substances, which is in line with previous research demonstrating that substance use may serve to dampen or decrease negative emotions (Cheetham et al., 2010; Measelle, Stice, & Springer, 2006). Despite affective reactivity increasing the likelihood of an individual reporting problematic substance use, it also appears to potentiate reward processing in the presence of emotional stimuli. As previously discussed, high levels of affective reactivity appear to increase task engagement following emotional pictures, resulting in a larger reward positivity. Additionally, these

individuals may be more sensitive to rewards or the pleasant emotion associated with receiving rewards. Taken together, affective reactivity may act to increase the sensitivity of the reward processing system previously observed to be impaired in substance dependent individuals. These results suggest two different populations of substance users: one that displays evidence of impaired reward processing, and another that is associated with increased reactivity and increased reward processing.

Better understanding of the psychological and biological risks for substance use may enable us to tailor treatment approaches for individuals struggling with SUDs. For instance, the results of the current study suggest that an individual with a SUD who is highly reactive to emotional stimuli might process emotions and rewards differently than a substance dependent individual with low affective reactivity. It remains to be seen if high levels of affective reactivity can be harnessed as a potentially protective factor against impaired reward processing, or if high affective reactivity increases risk for substance misuse above and beyond the risk associated with impaired reward processing.

Limitations and Future Directions

The primary limitation of the current study was low rates of self-reported substance use resulting in low power and the inability to replicate observations of a reduced reward positivity in individuals reporting high risk substance use. This prevented me from being able to explore the impact of individual differences in affective instability on impaired reward processing previously observed in substance dependent individuals. Despite this limitation, the current study did find a relationship between affective reactivity, increased substance use, and increased sensitivity to reward feedback following emotionally valent pictures. Future studies are needed to elucidate the precise relationship between reactivity and impaired reward processing in substance dependent

individuals. Without first replicating the observation of impaired reward processing in individuals reporting substance misuse, it is not possible to determine whether affective reactivity acts to increase risk for substance dependence, or perhaps is a protective factor by increasing sensitivity to naturally occurring rewards.

Other limitations include the fact that the questionnaires assessing substance use and individual differences were all based on self-report, which can be inaccurate. Additionally, participants were not screened with regard to personality and psychological disorders (i.e., substances use disorder, borderline personality disorder, major depressive disorder), thus correlations between questionnaires could have been influenced by individuals with clinical diagnoses or maladaptive personality traits. While this is less concerning following the RDoC approach, it still leaves the possibility that the observed relationships were influenced by constructs that were not measured in the current study. Finally, the participants were not asked to rate their subjective level of arousal in response to the specific IAPS stimuli used in the current study, which limited my ability to determine the relationship between self-reported affective reactivity and self-reported levels of emotional arousal. Future studies might include an assessment of arousal in response to task-specific emotional stimuli in order to relate this to affective reactivity.

Concluding Remarks

The current study sought to examine dimensions of affective instability in a non-clinical sample and to determine how affective instability impacts substance use and the neural mechanisms of reward and emotion processing. I found evidence for a unique relationship between affective lability, urgency, and impulsivity (affective reactivity) that predicted higher rates of substance use in an undergraduate student population. I also found evidence that individuals reporting higher levels of reactivity demonstrated increased reward processing following

emotional stimuli. These results suggest individual differences in affective reactivity impact neural mechanisms of reward processing. Although the current study lacked sufficient statistical power to replicate the observation of a smaller reward positivity in substance dependent individuals, the results support the notion that there are multiple paths to problematic substance use, and that affective reactivity should be considered when assessing and treating SUDs. Further, my results suggest that individual differences in affective reactivity may reflect a component of reward sensitivity as demonstrated through differences in the amplitude of the reward positivity. As the RDoC framework gains momentum, it will become increasingly important to understand how the expression of individual differences span from typical to extreme and how these traits contribute to symptoms such as affective instability, which is observed across various disorders.

References

- Aas, M., Pedersen, G., Henry, C., Bjella, T., Bellivier, F., Leboyer, M., ... Etain, B. (2015). Psychometric properties of the Affective Lability Scale (54 and 18-item version) in patients with bipolar disorder, first-degree relatives, and healthy controls. *Journal of Affective Disorders, 172*, 375380. doi:10.1016/j.jad.2014.10.028
- American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). Arlington, VA: American Psychiatric Publishing.
- Arcos, F., Verdejo-García, A., Ceverino, A., Montañez-Pareja, M., López-Juárez, E., Sánchez-Barrera, M., ... Pérez-García, M. (2008). Dysregulation of emotional response in current and abstinent heroin users: negative heightening and positive blunting. *Psychopharmacology, 198*(2), 159–166.
- Auerbach, R., Tarlow, N., Bondy, E., Stewart, J., Aguirre, B., Kaplan, C., ... Pizzagalli, D. (2016). Electrocortical reactivity during self-referential processing in female youth with borderline personality disorder. *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging, 1*(4), 335–344. doi:10.1016/j.bpsc.2016.04.004
- Bagozzi, R. P., & Moore, D. J. (2011). On the dimensionality and construct validity of the Affect Intensity Measure. *TPM-Testing, Psychometrics, Methodology in Applied Psychology, 8*(1), 3–18.
- Baker, T. (2012). *Genetics, drugs, and cognitive control: Uncovering individual differences in substance dependence*. University of Victoria.
- Baker, T., & Holroyd, C. (2009). Which way do I go? Neural activation in response to feedback and spatial processing in a virtual T-maze. *Cerebral Cortex, 19*(8), 1708–1722. doi:10.1093/cercor/bhn223

- Baker, T., & Holroyd, C. (2015). Impaired RPE signaling in substance dependence. Comment on Parvaz et al. *Journal of Neuroscience*.
- Baker, T., Lesperance, P., Tucholka, A., Potvin, S., Larcher, K., Zhang, Y., ... Conrod, P. (2017). Reversing the atypical valuation of drug and nondrug rewards in smokers using multi-modal neuroimaging. *Biological Psychiatry*. doi:10.1016/j.biopsych.2017.01.015
- Baker, T., Stockwell, T., Barnes, G., Haesevoets, R., & Holroyd, C. (2016). Reward sensitivity of ACC as an intermediate phenotype between DRD4-521T and substance misuse. *Journal of Cognitive Neuroscience*, 28(3), 460–471. doi:10.1162/jocn_a_00905
- Baker, T., Stockwell, T., Barnes, G., & Holroyd, C. (2011). Individual differences in substance dependence: at the intersection of brain, behaviour and cognition. *Addiction Biology*, 16(3), 458–466. doi:10.1111/j.1369-1600.2010.00243.x
- Baker, T., Stockwell, T., & Holroyd, C. (2013). Constraints on decision making: Implications from genetics, personality, and addiction. *Cognitive, Affective, & Behavioral Neuroscience*. doi:10.3758/s13415-013-0164-8
- Baker, T., Wood, J., & Holroyd, C. (2016). Atypical valuation of monetary and cigarette rewards in substance dependent smokers. *Clinical Neurophysiology*, 127(2), 1358–1365. doi:10.1016/j.clinph.2015.11.002
- Baler, R., & Volkow, N. (2006). Drug addiction: the neurobiology of disrupted self-control. *Trends in Molecular Medicine*, 12(12), 559–566. doi:10.1016/j.molmed.2006.10.005
- Baskin-Sommers, A., & Foti, D. (2015). Abnormal reward functioning across substance use disorders and major depressive disorder: Considering reward as a transdiagnostic

- mechanism. *International Journal of Psychophysiology*, 98(2), 227–239.
doi:10.1016/j.ijpsycho.2015.01.011
- Berking, M., & Wupperman, P. (2012). Emotion regulation and mental health: recent findings, current challenges, and future directions. *Current Opinion in Psychiatry*, 25(2), 128.
doi:10.1097/ycp.0b013e3283503669
- Berridge, K., & Robinson, T. (1998). What is the role of dopamine in reward: hedonic impact, reward learning, or incentive salience
- Bismark, A., Hajcak, G., Whitworth, N., & Allen, J. (2013). The role of outcome expectations in the generation of the feedback-related negativity. *Psychophysiology*, 50(2), 125–133.
doi:10.1111/j.1469-8986.2012.01490.x
- Bissonette, G., & Roesch, M. (2016). Development and function of the midbrain dopamine system: what we know and what we need to. *Genes, Brain and Behavior*, 15(1), 62–73.
doi:10.1111/gbb.12257
- Botella, M., Zenasni, F., & Lubart, T. (2011). Alexithymia and affect intensity of art students. *Psychology of Aesthetics, Creativity, and the Arts*, 5(3), 251. doi:10.1037/a0022311
- Bress, J., & Hajcak, G. (2013). Self-report and behavioral measures of reward sensitivity predict the feedback negativity. *Psychophysiology*, 50(7), 610–616. doi:10.1111/psyp.12053
- Britton, J., Taylor, S., Sudheimer, K., & Liberzon, I. (2006). Facial expressions and complex IAPS pictures: Common and differential networks. *NeuroImage*, 31(2), 906–919.
doi:10.1016/j.neuroimage.2005.12.050
- Brosch, T., Pourtois, G., & Sander, D. (2010). The perception and categorisation of emotional stimuli: A review. *Cognition & Emotion*, 24(3), 377–400.
doi:10.1080/02699930902975754

- Brown, J. W. (2017). Models of anterior cingulate cortex function in cognitive control. wiley. doi:10.1002/9781118920497.ch15
- Brown, S., van Steenbergen, H., Band, G., de Rover, M., & Nieuwenhuis, S. (2012). Functional significance of the emotion-related late positive potential. *Frontiers in Human Neuroscience*, 6, 33. doi:10.3389/fnhum.2012.00033
- Carpenter, R., & Trull, T. (2013). Components of emotion dysregulation in borderline personality disorder: A review. *Current Psychiatry Reports*, 15(1), 335. doi:10.1007/s11920-012-0335-2
- Castellanos-Ryan, N., O'Leary-Barrett, M., Sully, L., & Conrod, P. (2013). Sensitivity and specificity of a brief personality screening instrument in predicting future substance use, emotional, and behavioral problems: 18-Month predictive validity of the substance use risk profile scale. *Alcoholism: Clinical and Experimental Research*, 37(s1), E281–E290. doi:10.1111/j.1530-0277.2012.01931.x
- Cheetham, A., Allen, N., Yücel, M., & Lubman, D. (2010). The role of affective dysregulation in drug addiction. *Clinical Psychology Review*, 30(6), 621–634. doi:10.1016/j.cpr.2010.04.005
- Chiara, D., & Imperato. (1988). Drugs abused by humans preferentially increase synaptic dopamine concentrations in the mesolimbic system of freely moving rats. *Proceedings of the National Academy of Sciences*, 85(14), 5274–5278. doi:10.1073/pnas.85.14.5274
- Chinta, S., & Andersen, J. (2005). Dopaminergic neurons. *The International Journal of Biochemistry & Cell Biology*, 37(5), 942–946. doi:10.1016/j.biocel.2004.09.009
- Codispoti, M., Ferrari, V., & Bradley, M. (2006). Repetitive picture processing: Autonomic and cortical correlates. *Brain Research*, 1068(1), 213–220. doi:10.1016/j.brainres.2005.11.009

- Cole, P., Michel, M., & Teti, L. (1994). The development of emotion regulation and dysregulation: A clinical perspective. *Monographs of the Society for Research in Child Development*, 59(2-3), 73-102. doi:10.1111/j.1540-5834.1994.tb01278.x
- Cools, R. (2008). Role of dopamine in the motivational and cognitive control of behavior. *The Neuroscientist*, 14(4), 381-395.
- Cooper, A., Duke, É., Pickering, A., & Smillie, L. (2014). Individual differences in reward prediction error: contrasting relations between feedback-related negativity and trait measures of reward sensitivity, impulsivity and extraversion. *Frontiers in Human Neuroscience*, 8, 248. doi:10.3389/fnhum.2014.00248
- Coskunpinar, A., Dir, A., & Cyders, M. (2013). Multidimensionality in impulsivity and alcohol use: A meta-analysis using the UPPS model of impulsivity. *Alcoholism: Clinical and Experimental Research*, 37(9), 1441–1450. doi:10.1111/acer.12131
- Coskunpinar, A., Dir, A., Karyadi, K., Koo, C., & Cyders, M. (2013). Mechanisms underlying the relationship between negative affectivity and problematic alcohol use. *Journal of Experimental Psychopathology*, 4(3), 263–278. doi:10.5127/jep.029612
- Cosme, D., & Wiens, S. (2015). Self-Reported trait mindfulness and affective reactivity: A motivational approach using multiple psychophysiological measures. *PLOS ONE*, 10(3), e0119466. doi:10.1371/journal.pone.0119466
- Cuthbert, B., Schupp, H., Bradley, M., Birbaumer, N., & Lang, P. (2000). Brain potentials in affective picture processing: covariation with autonomic arousal and affective report. *Biological Psychology*, 52(2), 95–111. doi:10.1016/S0301-0511(99)00044-7
- Cyders, M. (2011). Impulsivity and the sexes: Measurement and structural invariance of the UPPS-P Impulsive Behavior Scale. *Assessment*, 20(1), 8697. doi:10.1177/1073191111428762

- Cyders, M., & Smith, G. (2007). Mood-based rash action and its components: Positive and negative urgency. *Personality and Individual Differences, 43*(4), 839–850. doi:10.1016/j.paid.2007.02.008
- Cyders, M., & Smith, G. (2008). Emotion-based dispositions to rash action: Positive and negative urgency. *Psychological Bulletin, 134*(6), 807. doi:10.1037/a0013341
- Cyders, M., Smith, G., Spillane, N., Fischer, S., Annus, A., & Peterson, C. (2007). Integration of impulsivity and positive mood to predict risky behavior: Development and validation of a measure of positive urgency. *Psychological Assessment, 19*(1), 107. doi:10.1037/1040-3590.19.1.107
- Di Chiara, G., & Bassareo, V. (2007). Reward system and addiction: what dopamine does and doesn't do. *Current Opinion in Pharmacology, 7*(1), 69–76. doi:10.1016/j.coph.2006.11.003
- Diana, M., & Tepper, J. (2002). Electrophysiological pharmacology of mesencephalic dopaminergic neurons. In *Dopamine in the CNS II* (pp. 1-61). Springer Berlin Heidelberg.
- Dietz, Bradley, M. M., Jones, Okun, Perlstein, W. M., & Bowers. (2013). The late positive potential, emotion and apathy in Parkinson's disease. *Neuropsychologia, 51*(5), 960–966. doi:10.1016/j.neuropsychologia.2013.01.001
- Dinc, L., & Cooper, A. (2015). Positive affective states and alcohol consumption: The moderating role of trait positive urgency. *Addictive Behaviors, 47*, 17–21. doi:10.1016/j.addbeh.2015.03.014
- Donchin, E., & Coles, M. G. (1988). Is the P300 component a manifestation of context updating?. *Behavioral and brain sciences, 11*(3), 357-374.

- Dum, R. P., & Strick, P. L. (1993). Cingulate motor areas. In B. A. Vogt & M. Gabriel (Eds.), *Neurobiology of cingulate cortex and limbic thalamus: A comprehensive handbook* (pp. 415–441). Boston: Birkhäuser.
- Duncan-Johnson, C. C., & Donchin, E. (1977). On quantifying surprise: The variation of event-related potentials with subjective probability. *Psychophysiology*, *14*(5), 456-467.
- Dunning, J., & Hajcak, G. (2009). See no evil: Directing visual attention within unpleasant images modulates the electrocortical response. *Psychophysiology*, *46*(1), 28–33. doi:10.1111/j.1469-8986.2008.00723.x
- Dunning, J., Parvaz, M., Hajcak, G., Maloney, T., Alia-Klein, N., Woicik, P., ... Goldstein, R. (2011). Motivated attention to cocaine and emotional cues in abstinent and current cocaine users – an ERP study. *European Journal of Neuroscience*, *33*(9), 1716–1723. doi:10.1111/j.1460-9568.2011.07663.x
- Ebitz, B., & Hayden, B. (2016). Dorsal anterior cingulate: a Rorschach test for cognitive neuroscience. *Nature Neuroscience*, *19*(10), 1278–1279. doi:10.1038/nn.4387
- Ebner-Priemer, U., Santangelo, P., & Bohus, M. (2016). Emotional instability and borderline personality disorder. *European Psychiatry*, *33*, S51. doi:10.1016/j.eurpsy.2016.01.920
- Engelmann, J., Versace, F., Gewirtz, J., & Cinciripini, P. (2016). Individual differences in brain responses to cigarette-related cues and pleasant stimuli in young smokers. *Drug and Alcohol Dependence*, *163*, 229–235. doi:10.1016/j.drugalcdep.2016.04.025
- Fein, G., & Chang, M. (2008). Smaller feedback ERN amplitudes during the BART are associated with a greater family history density of alcohol problems in treatment-naïve alcoholics. *Drug and Alcohol Dependence*, *92*(1-3), 141–148. doi:10.1016/j.drugalcdep.2007.07.017

- Ferri, J., Weinberg, A., & Hajcak, G. (2012). I see people: The presence of human faces impacts the processing of complex emotional stimuli. *Social Neuroscience*, 7(4), 436–443. doi:10.1080/17470919.2012.680492
- Fischer, S., & Smith, G. (2008). Binge eating, problem drinking, and pathological gambling: Linking behavior to shared traits and social learning. *Personality and Individual Differences*, 44(4), 789–800. doi:10.1016/j.paid.2007.10.008
- Flett, G., & Hewitt, P. (1995). Criterion validity and psychometric properties of the affect intensity measure in a psychiatric sample. *Personality and Individual Differences*, 19(4), 585–591. doi:10.1016/0191-8869(95)00089-o
- Foti, D., & Hajcak, G. (2010). State sadness reduces neural sensitivity to nonrewards versus rewards. *NeuroReport*, 21(2), 143. doi:10.1097/wnr.0b013e3283356448
- Foti, D., Weinberg, A., Dien, J., & Hajcak, G. (2011). Event-related potential activity in the basal ganglia differentiates rewards from nonrewards: Temporospacial principal components analysis and source localization of the feedback negativity. *Human Brain Mapping*, 32(12), 2207–2216. doi:10.1002/hbm.21182
- Franken, I., Dietvorst, R., Hesselmann, M., Franzek, E., Wetering, B., & Strien, J. (2008). Clinical Study: Cocaine craving is associated with electrophysiological brain responses to cocaine-related stimuli. *Addiction Biology*, 13(3-4), 386–392. doi:10.1111/j.1369-1600.2008.00100.x
- Gradin, V., Baldacchino, A., Balfour, D., Matthews, K., & Steele, D. (2013). Abnormal brain activity during a reward and loss task in opiate-dependent patients receiving methadone maintenance therapy. *Neuropsychopharmacology*, 39(4), 885–894. doi:10.1038/npp.2013.289

- Gratton, G., Coles, M., & Donchin, E. (1983). A new method for off-line removal of ocular artifact. *Electroencephalography and clinical neurophysiology*, *55*(4), 468–84. doi:10.1016/0013-4694(83)90135-9
- Gross, J. J., & Thompson, R. A. (2007). *Emotion regulation: Conceptual foundations*. New York, NY: Guilford Press.
- Hajcak, G., Dunning, J., & Foti, D. (2009). Motivated and controlled attention to emotion: time-course of the late positive potential. *Clinical Neurophysiology*, *120*(3), 505–510.
- Hajcak, G., MacNamara, A., & Olvet, D. (2010). Event-Related potentials, emotion, and emotion regulation: An integrative review. *Developmental Neuropsychology*, *35*(2), 129–155. doi:10.1080/87565640903526504
- Hajcak, G., Weinberg, A., MacNamara, A., & Foti, D. (2012). ERPs and the study of emotion. *The Oxford handbook of event-related potential components*, 441-474.
- Hariri, A., Tessitore, A., Mattay, V., Fera, F., & Weinberger, D. (2002). The amygdala response to emotional stimuli: A comparison of faces and scenes. *NeuroImage*, *17*(1), 317–323. doi:10.1006/nimg.2002.1179
- Harvey, P., Greenberg, B., & Serper, M. (1989). The affective lability scales: development, reliability, and validity. *Journal of clinical psychology*, *45*(5), 786–93.
- Hasin, D., Fenton, M. C., Skodol, A., Krueger, R., Keyes, K., Geier, T., ... Grant, B. (2011). Personality disorders and the 3-year course of alcohol, drug, and nicotine use disorders. *Archives of General Psychiatry*, *68*(11), 1158–1167.
- Hauser, T., Iannaccone, R., Stämpfli, P., Drechsler, R., Brandeis, D., Walitza, S., & Brem, S. (2014). The feedback-related negativity (FRN) revisited: New insights into the

- localization, meaning and network organization. *NeuroImage*, *84*, 159–168.
doi:10.1016/j.neuroimage.2013.08.028
- Holroyd, C., & Coles, M. (2002). The neural basis of human error processing: Reinforcement learning, dopamine, and the error-related negativity. *Psychological Review*, *109*(4), 679.
doi:10.1037/0033-295X.109.4.679
- Holroyd, C., & Krigolson, O. (2007). Reward prediction error signals associated with a modified time estimation task. *Psychophysiology*, *44*(6), 913–917. doi:10.1111/j.1469-8986.2007.00561.x
- Holroyd, C., & McClure, S. (2015). Hierarchical control over effortful behavior by rodent medial frontal cortex: A computational model. *Psychological Review*, *122*(1), 54–83.
doi:10.1037/a0038339
- Holroyd, C., Pakzad-Vaezi, K., & Krigolson, O. (2008). The feedback correct-related positivity: Sensitivity of the event-related brain potential to unexpected positive feedback. *Psychophysiology*, *45*(5), 688–697. doi:10.1111/j.1469-8986.2008.00668.x
- Holroyd, C., & Umemoto, A. (2016). The research domain criteria framework: The case for anterior cingulate cortex. *Neuroscience & Biobehavioral Reviews*, *71*, 418–443.
doi:10.1016/j.neubiorev.2016.09.021
- Holroyd, C., & Yeung, N. (2012). Motivation of extended behaviors by anterior cingulate cortex. *Trends in Cognitive Sciences*, *16*(2), 122–128. doi:10.1016/j.tics.2011.12.008
- Humeniuk, R., Henry-Edwards, S., Ali, R., & Poznyak, V. (2010). The Alcohol, Smoking and Substance Involvement Screening Test (ASSIST): manual for use in primary care.

- Humeniuk, R., Ali, R., Babor, T., Farrell, M., Formigoni, M., Jittiwutikarn, J., ... Simon, S. (2008). Validation of the alcohol, smoking and substance involvement screening test (ASSIST). *Addiction, 103*(6), 1039–1047. doi:10.1111/j.1360-0443.2007.02114.x
- Hyman, S. (2007). The neurobiology of addiction: Implications for voluntary control of behavior. *The American Journal of Bioethics, 7*(1), 8–11. doi:10.1080/15265160601063969
- Ireland, N. (2016, December 6). The year of the fentanyl crisis: How we got here. *CBC News: Health*. CBC News: Health.
- Jaffe, J. H., & Jaffe, F. K. (1989). Historical perspectives on the use of subjective effects measures in assessing the abuse potential of drugs. *NIDA Research Monograph, 92*, 43–72.
- Jones, K. D., Gill, C., & Ray, S. (2012). Review of the proposed DSM-5 substance use disorder. doi:10.1002/j.2161-1874.2012.00009.x
- Kassel, J. D., Veilleux, J. C., Wardle, M. C., Yates, M. C., Greenstein, J. E., Evatt, D. P., & Roesch, L. L. (2007). Negative affect and addiction. *Stress and addiction: Biological and psychological mechanisms*, 171-189.
- Katahira, K., Matsuda, Y.-T., Fujimura, T., Ueno, K., Asamizuya, T., Suzuki, C., ... Okada, M. (2015). Neural basis of decision making guided by emotional outcomes. *Journal of neurophysiology, 113*(9), 3056–3068. doi:10.1152/jn.00564.2014
- Kelley, A. E. (2005). Neurochemical networks encoding emotion and motivation: An evolutionary perspective. (pp. 29–77). New York, NY: Oxford University Press.
- Kober, H. (2014). Emotion regulation in substance use disorders (2nd ed., p. 428–446). New York, NY: Guilford PRes.

- Koenigsberg, H. (2010). Affective instability: toward an integration of neuroscience and psychological perspectives. *Journal of personality disorders*, 24(1), 60–82. doi:10.1521/pedi.2010.24.1.60
- Koenigsberg, Siever, Lee, & Pizzarello. (2009). Neural correlates of emotion processing in borderline personality disorder. doi:10.1016/j.psychresns.2008.07.010
- Koob, G., & Le Moal, M. (1997). Drug abuse: hedonic homeostatic dysregulation. *Science*, 278(5335), 52-58.
- Koob, G., & Moal, M. (2008). Neurobiological mechanisms for opponent motivational processes in addiction. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, 363(1507), 3113–3123. doi:10.1098/rstb.2008.0094
- Koole, S. (2009). The psychology of emotion regulation: An integrative review. *Cognition & Emotion*, 23(1), 4–41. doi:10.1080/02699930802619031
- Kozak, M., & Cuthbert, B. (2016). The NIMH research domain criteria Initiative: Background, issues, and pragmatics. *Psychophysiology*, 53(3), 286–297. doi:10.1111/psyp.12518
- Krigolson, O., Hassall, C., & Handy, T. (2013). How we learn to make decisions: Rapid propagation of reinforcement learning prediction errors in humans. *Journal of Cognitive Neuroscience*, 110. doi:10.1162/jocn_a_00509
- Krueger, R., Derringer, J., Markon, K., Watson, D., & Skodol, A. (2011). Initial construction of a maladaptive personality trait model and inventory for DSM-5. *Psychological Medicine*, 42(9), 1879–1890. doi:10.1017/S0033291711002674
- Kujawa, A., Hajcak, G., Torpey, D., Kim, J., & Klein, D. (2012). Electro cortical reactivity to emotional faces in young children and associations with maternal and paternal depression.

- Journal of Child Psychology and Psychiatry*, 53(2), 207–215. doi:10.1111/j.1469-7610.2011.02461.x
- Kuo, J., & Linehan, M. (2009). Disentangling emotion processes in borderline personality disorder: Physiological and self-reported assessment of biological vulnerability, baseline intensity, and reactivity to emotionally evocative stimuli. *Journal of abnormal psychology*, 118(3), 531.
- Lagerberg, T., Aminoff, S., Aas, M., Bjella, T., Henry, C., Leboyer, M., ... Melle, I. (2017). Alcohol use disorders are associated with increased affective lability in bipolar disorder. *Journal of Affective Disorders*, 208, 316–324. doi:10.1016/j.jad.2016.09.062
- Lang, P. (2010). Emotion and motivation: Toward consensus definitions and a common research purpose. *Emotion Review*, 2(3), 229–233. doi:10.1177/1754073910361984
- Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (2008). International affective picture system (IAPS): Affective ratings of pictures and instruction manual. Technical Report A-8. University of Florida, Gainesville, FL.
- Larsen, R., & Diener, E. (1987). Affect intensity as an individual difference characteristic: A review. *Journal of Research in Personality*, 21(1), 139. doi:10.1016/0092-6566(87)90023-7
- Li, P., Han, C., Lei, Y., Holroyd, C., & Li, H. (2011). Responsibility modulates neural mechanisms of outcome processing: An ERP study. *Psychophysiology*, 48(8), 1129–1133. doi:10.1111/j.1469-8986.2011.01182.x
- Littel, M., Euser, A., Munafò, M., & Franken, I. (2012). Electrophysiological indices of biased cognitive processing of substance-related cues: A meta-analysis. *Neuroscience & Biobehavioral Reviews*, 36(8), 1803–1816. doi:10.1016/j.neubiorev.2012.05.001

- Liu, W., Wang, L., Shang, H., Shen, Y., Li, Z., Cheung, E., & Chan, R. (2014). The influence of anhedonia on feedback negativity in major depressive disorder. *Neuropsychologia*, *53*, 213–220. doi:10.1016/j.neuropsychologia.2013.11.023
- Liu, Y., Huang, H., McGinnis-Deweese, M., Keil, A., & Ding, M. (2012). Neural substrate of the late positive potential in emotional processing. *The Journal of Neuroscience*, *32*(42), 14563–14572. doi:10.1523/JNEUROSCI.3109-12.2012
- Ljunberg, T., Apicella, P., & Schultz, W. (1991). Responses of monkey midbrain dopamine neurons during delayed alternation performance. *Brain Research*, *567*(2), 337-341.
- Look, A., Flory, J., Harvey, P., & Siever, L. (2010). Psychometric properties of a short form of the Affective Lability Scale (ALS-18). *Personality and Individual Differences*, *49*(3), 187–191. doi:10.1016/j.paid.2010.03.030
- Luck, S. J. (2012). *Event-related potentials*. Washington, DC: American Psychological Association.
- Lukie, C., Montazer-Hojat, S., & Holroyd, C. (2014). Developmental changes in the reward positivity: An electrophysiological trajectory of reward processing. *Developmental Cognitive Neuroscience*, *9*. doi:10.1016/j.dcn.2014.04.003
- MacNamara, A., & Hajcak, G. (2010). Distinct electrocortical and behavioral evidence for increased attention to threat in generalized anxiety disorder. *Depression and Anxiety*, *27*(3), 234–243. doi:10.1002/da.20679
- MacNamara, A., Kotov, R., & Hajcak, G. (2015). Diagnostic and symptom-based predictors of emotional processing in generalized anxiety disorder and major depressive disorder: An event-related potential study. *Cognitive Therapy and Research*. doi:10.1007/s10608-015-9717-1

- MacNamara, A., & Hajcak, G. (2009). Anxiety and spatial attention moderate the electrocortical response to aversive pictures.
- Marissen, M., Meuleman, L., & Franken, I. (2010). Altered emotional information processing in borderline personality disorder: An electrophysiological study. *Psychiatry Research: Neuroimaging*, *181*(3), 226–232. doi:10.1016/j.psychresns.2009.10.006
- Martin, L., & Potts, G. (2011). Medial frontal event-related potentials and reward prediction: Do responses matter? *Brain and Cognition*, *77*(1), 128–134. doi:10.1016/j.bandc.2011.04.001
- Marwaha, S., He, Z., Broome, M., Singh, S., Scott, J., Eyden, J., & Wolke, D. (2014). How is affective instability defined and measured? A systematic review. *Psychological Medicine*, *44*(9), 1793–1808. doi:10.1017/S0033291713002407
- Measelle, J., Stice, E., & Springer, D. (2006). A prospective test of the negative affect model of substance abuse: moderating effects of social support. *Psychology of Addictive Behaviors*, *20*(3), 225.
- Michalowski, J., Pané-Farré, C., Löw, A., & Hamm, A. (2015). Brain dynamics of visual attention during anticipation and encoding of threat- and safe-cues in spider-phobic individuals. *Social Cognitive and Affective Neuroscience*, *10*(9), 1177–1186. doi:10.1093/scan/nsv002
- Miltner, W., Braun, C., & Coles, M. (1997). Event-related brain potentials following incorrect feedback in a time-estimation task: evidence for a “generic” neural system for error detection. *Journal of cognitive neuroscience*, *9*(6), 788–98. doi:10.1162/jocn.1997.9.6.788
- Minnix, J., Versace, F., Robinson, J., Lam, C., Engelmann, J., Cui, Y., ... Cinciripini, P. (2013). The late positive potential (LPP) in response to varying types of emotional and cigarette stimuli in smokers: A content comparison. *International Journal of Psychophysiology*, *89*(1), 18–25. doi:10.1016/j.ijpsycho.2013.04.019

- Montague, P. R., Dayan, P., & Sejnowski, T. J. (1996). A framework for mesencephalic dopamine systems based on predictive hebbian learning. *Journal of Neuroscience*, *16*, 1936-1947.
- Montague, P., Hyman, S., Cohen, J. (2004). Computational roles for dopamine in behavioural control. *Nature*, *431(7010)*, 760-767.
- Morey, L., Hopwood, C., Gunderson, J., Skodol, A., Shea, M., Yen, S., ... McGlashan, T. (2006). Comparison of alternative models for personality disorders. *Psychological Medicine*, *37(7)*, 983–994. doi:10.1017/S0033291706009482
- Mulligan, K., & Scherer, K. (2012). Toward a working definition of emotion. *Emotion Review*, *4(4)*, 345–357. doi:10.1177/1754073912445818
- Newcombe, D. A., Humeniuk, R. E., & Ali, R. (2005). Validation of the world health organization alcohol, smoking and substance involvement screening test (ASSIST): report of results from the Australian site. *Drug and alcohol review*, *24(3)*, 217-226.
- Nica, E., & Links, P. (2009). Affective instability in borderline personality disorder: Experience sampling findings. *Current psychiatry reports*, *11(1)*, 74–81.
- Oliver, M., & Simons, J. (2004). The affective lability scales: Development of a short-form measure. *Personality and Individual Differences*, *37(6)*, 1279-1288. doi:10.1016/j.paid.2003.12.013
- Onoda, K., Abe, S., & Yamaguchi, S. (2010). Feedback-related negativity is correlated with unplanned impulsivity. *NeuroReport*, *21(10)*, 736. doi:10.1097/WNR.0b013e32833bfd36
- Palermo, R., & Rhodes, G. (2007). Are you always on my mind? A review of how face perception and attention interact. *Neuropsychologia*, *45(1)*, 75–92. doi:10.1016/j.neuropsychologia.2006.04.025

- Park, S., Kahnt, T., Beck, A., Cohen, M., Dolan, R., Wrase, J., & Heinz, A. (2010). Prefrontal cortex fails to learn from reward prediction errors in alcohol dependence. *The Journal of Neuroscience*, *30*(22), 7749–7753. doi:10.1523/JNEUROSCI.5587-09.2010
- Parvaz, M., Gabbay, V., Malaker, P., & Goldstein, R. (2016). Objective and specific tracking of anhedonia via event-related potentials in individuals with cocaine use disorders. *Drug and Alcohol Dependence*, *164*, 158–165. doi:10.1016/j.drugalcdep.2016.05.004
- Parvaz, M., Konova, A., Proudfit, G., Dunning, J., Malaker, P., Moeller, S., ... Goldstein, R. (2015). Impaired neural response to negative prediction errors in cocaine addiction. *The Journal of Neuroscience*, *35*(5), 1872–1879. doi:10.1523/JNEUROSCI.2777-14.2015
- Paus, T. (2001). Primate anterior cingulate cortex: where motor control, drive and cognition interface. *Nature reviews neuroscience*, *2*(6).
- Pearson, C., Janz, T., & Ali, J. (2012). *Mental and substance use disorders in Canada*. Statistics Canada.
- Pearson, M., Lawless, A., Brown, D., & Bravo, A. (2015). Mindfulness and emotional outcomes: Identifying subgroups of college students using latent profile analysis. *Personality and Individual Differences*, *76*, 33–38. doi:10.1016/j.paid.2014.11.009
- Peterburs, J., Kobza, S., & Bellebaum, C. (2016). Feedback delay gradually affects amplitude and valence specificity of the feedback-related negativity (FRN). *Psychophysiology*, *53*(2), 209–215. doi:10.1111/psyp.12560
- Proudfit, G. (2015). The reward positivity: From basic research on reward to a biomarker for depression. *Psychophysiology*, *52*(4), 449–459. doi:10.1111/psyp.12370

- Rankin, L., & Maggs, J. (2006). First-year college student affect and alcohol use: Paradoxical within- and between-person associations. *Journal of Youth and Adolescence*, *35*(6), 925–937. doi:10.1007/s10964-006-9073-2
- Redish, D., Jensen, S., & Johnson, A. (2008). A unified framework for addiction: Vulnerabilities in the decision process. *Behavioral and Brain Sciences*, *31*(04). doi:10.1017/S0140525X0800472X
- Rehm, J., Gnam, W., Popova, S., Baliunas, D., Brochu, S., Fischer, B., Patra, J., Sarnocinska-Hart, A., & Taylor, B. (2007). The costs of alcohol, illegal drugs, and tobacco in Canada, 2002. *Journal of studies on alcohol and drugs*, *68*(6), 886–95.
- Rehm, J., Taylor, B., & Room, R. (2006). Global burden of disease from alcohol, illicit drugs and tobacco. *Drug and Alcohol Review*, *25*(6), 503–513. doi:10.1080/09595230600944453
- Renaud, S., & Zacchia, C. (2012). Toward a definition of affective instability. *Harvard Review of Psychiatry*, *20*(6), 298. doi:10.3109/10673229.2012.747798
- Richards, A., Holmes, A., Pell, P., & Bethell, E. (2013). Adapting effects of emotional expression in anxiety: Evidence for an enhanced Late Positive Potential. *Social Neuroscience*, *8*(6), 650–664. doi:10.1080/17470919.2013.854273
- Riepl, K., Mussel, P., Osinsky, R., & Hewig, J. (2016). Influences of state and trait affect on behavior, feedback-related negativity, and P3b in the ultimatum game. *PLOS ONE*, *11*(1), e0146358. doi:10.1371/journal.pone.0146358
- Rose, E., Ross, T., Salmeron, B., Lee, M., Shakleya, D., Huestis, M., & Stein, E. (2012). Chronic exposure to nicotine is associated with reduced reward-related activity in the striatum but not the midbrain. *Biological Psychiatry*, *71*(3), 206–213. doi:10.1016/j.biopsych.2011.09.013

- Rose, E., Salmeron, B., Ross, T., Waltz, J., Schweitzer, J., McClure, S., & Stein, E. (2014). Temporal difference error prediction signal dysregulation in cocaine dependence. *Neuropsychopharmacology*, *39*(7), 1732–1742. doi:10.1038/npp.2014.21
- Rubin, D., Hoyle, R., & Leary, M. (2011). Differential predictability of four dimensions of affect intensity. *Cognition & emotion*, *26*(1), 25–41. doi:10.1080/02699931.2011.561564
- Sambrook, T., & Goslin, J. (2015). A neural reward prediction error revealed by a meta-analysis of ERPs using great grand averages. *Psychological Bulletin*, *141*(1), 213. doi:10.1037/bul0000006
- Scharmüller, W., Leutgeb, V., Schäfer, A., Köchel, A., & Schienle, A. (2011). Source localization of late electrocortical positivity during symptom provocation in spider phobia: An sLORETA study. *Brain Research*, *1397*, 10–18. doi:10.1016/j.brainres.2011.04.018
- Schimmack, U. (2012). The ironic effect of significant results on the credibility of multiple-study articles. *Psychological Methods*, *17*(4), 551–566. doi:10.1037/a0029487
- Schmidt, B., Holroyd, C., Debener, S., & Hewig, J. (2017). I can't wait! Neural reward signals in impulsive individuals exaggerate the difference between immediate and future rewards. *Psychophysiology*, *54*(3), 409–415. doi:10.1111/psyp.12796
- Schultz, W. (2002). Getting formal with dopamine and reward. *Neuron*, *36*(2), 241-263.
- Schultz, W., Apicella, P., & Ljungberg, T. (1993). Responses of monkey dopamine neurons to reward and conditioned stimuli during successive steps of learning a delayed response task. *Journal of Neuroscience*, *13*(3), 900-913.
- Schultz, W., Dayan, P., Montague, P. (1997). A neural substrate of prediction and reward. *Science*, *275*(5306), 1593-1599.

- Schulze, L., Domes, G., Krüger, A., Berger, C., Fleischer, M., Prehn, K., ... Herpertz, S. (2011). Neuronal correlates of cognitive reappraisal in borderline patients with affective instability. *Biological Psychiatry*, *69*(6), 564–573. doi:10.1016/j.biopsych.2010.10.025
- Schupp, H., Cuthbert, B., Bradley, M., Cacioppo, J., Ito, T., & Lang, P. (2000). Affective picture processing: The late positive potential is modulated by motivational relevance. *Psychophysiology*, *37*(2), 257–261. doi:10.1111/1469-8986.3720257
- Shenhav, A., Botvinick, M., & Cohen, J. (2013). The Expected value of control: An integrative theory of Anterior Cingulate Cortex function. *Neuron*, *79*(2), 217–240. doi:10.1016/j.neuron.2013.07.007
- Sheppes, G., Suri, G., & Gross, J. (2015). Emotion regulation and psychopathology. *Annual Review of Clinical Psychology*, *11*(1), 379–405. doi:10.1146/annurev-clinpsy-032814-112739
- Silvers, J., Hubbard, A., Biggs, E., Shu, J., Fertuck, E., Chaudhury, S., ... Stanley, B. (2016). Affective lability and difficulties with regulation are differentially associated with amygdala and prefrontal response in women with Borderline Personality Disorder. *Psychiatry Research: Neuroimaging*, *254*, 74–82. doi:10.1016/j.psychresns.2016.06.009
- Simons, J., Carey, K., Wills, T., Simons, J., Carey, K., & Wills, T. (2009). Alcohol abuse and dependence symptoms: A multidimensional model of common and specific etiology. *Psychology of Addictive Behaviors*. doi:10.1037/a0016003
- Simons, J., Oliver, M., Gaher, R., Ebel, G., & Brummels, P. (2005). Methamphetamine and alcohol abuse and dependence symptoms: Associations with affect lability and impulsivity in a rural treatment population. *Addictive Behaviors*, *30*(7), 13701381. doi:10.1016/j.addbeh.2005.01.018

- Smillie, L., Cooper, A., & Pickering, A. (2011). Individual differences in reward–prediction–error: extraversion and feedback-related negativity. *Social Cognitive and Affective Neuroscience*, 6(5), 646–652. doi:10.1093/scan/nsq078
- Speed, B., Nelson, B., Perlman, G., Klein, D., Kotov, R., & Hajcak, G. (2015). Personality and emotional processing: A relationship between extraversion and the late positive potential in adolescence. *Psychophysiology*, 52(8), 1039–1047. doi:10.1111/psyp.12436
- Suri, R. E. (2002). TD models of reward predictive responses in dopamine neurons. *Neural Networks*, 15(4), 523-533.
- Sutton, S., Braren, M., Zubin, J., & John, E. (1965). Evoked-potential correlates of stimulus uncertainty.
- Sutton, R.S., & Barto, A.G. (1998). Reinforcement learning: An introduction. Cambridge, MA: MIT Press. Retrieved from [http://www.cell.com/trends/cognitive-sciences/pdf/S1364-6613\(99\)01331-5.pdf](http://www.cell.com/trends/cognitive-sciences/pdf/S1364-6613(99)01331-5.pdf)
- Suzuki, T., Samuel, D., Pahlen, S., & Krueger, R. (2015). DSM-5 alternative personality disorder model traits as maladaptive extreme variants of the five-factor model: An item-response theory analysis. *Journal of Abnormal Psychology*, 124(2), 343–354. doi:10.1037/abn0000035
- Tabachnick, B. G., & Fidell, L. S. (2007). Principal components and factor analysis (5th ed., pp. 607–675). United States of America: Pearson Education Inc.
- Tanabe, J., Reynolds, J., Krmpotich, T., Claus, E., Thompson, L., Du, Y., & Banich, M. (2013). Reduced neural tracking of prediction error in substance-dependent individuals. *American Journal of Psychiatry*, 170(11), 1356–1363. doi:10.1176/appi.ajp.2013.12091257

- Thorberg, F., & Lyvers, M. (2006). Negative Mood Regulation (NMR) expectancies, mood, and affect intensity among clients in substance disorder treatment facilities. *Addictive Behaviors, 31*(5), 811-820. doi:10.1016/j.addbeh.2005.06.008
- Threadgill, H., & Gable, P. (2016). Approach-motivated pregoal states enhance the reward positivity. *Psychophysiology, 53*(5), 733–738. doi:10.1111/psyp.12611
- Umemoto, A., HajiHosseini, A., Yates, M., & Holroyd, C. (2017). Reward-based contextual learning supported by anterior cingulate cortex. *Cognitive, Affective, & Behavioral Neuroscience, 17*(3), 642–651. doi:10.3758/s13415-017-0502-3
- Umemoto, A., & Holroyd, C. (2017). Neural mechanisms of reward processing associated with depression-related personality traits. *Clinical Neurophysiology, 128*(7), 1184–1196. doi:10.1016/j.clinph.2017.03.049
- Veilleux, J., Skinner, K., Reese, E., & Shaver, J. (2014). Negative affect intensity influences drinking to cope through facets of emotion dysregulation. *Personality and Individual Differences, 59*, 96–101. doi:10.1016/j.paid.2013.11.012
- Verrico, C., Haile, C., Newton, T., Kosten, T., Garza, R., & Garza, R. (2013). Pharmacotherapeutics for substance-use disorders: a focus on dopaminergic medications. *Expert Opinion on Investigational Drugs, 22*(12), 1549–1568. doi:10.1517/13543784.2013.836488
- Versace, F., Lam, C., Engelmann, J., Robinson, J., Minnix, J., Brown, V., & Cinciripini, P. (2012). Beyond cue reactivity: blunted brain responses to pleasant stimuli predict long-term smoking abstinence. *Addiction Biology, 17*(6), 991–1000. doi:10.1111/j.1369-1600.2011.00372.x

- Volkow, N. D., & Baler, R. D. (2014). Addiction science: Uncovering neurobiological complexity. *Neuropharmacology*, *76*, 235–249. doi:10.1016/j.neuropharm.2013.05.007
- Walsh, M., & Anderson, J. (2012). Learning from experience: Event-related potential correlates of reward processing, neural adaptation, and behavioral choice. *Neuroscience & Biobehavioral Reviews*, *36*(8), 1870–1884. doi:10.1016/j.neubiorev.2012.05.008
- Wang, Y., Gu, R., Luo, Y., & Zhou, C. (2017). The interaction between state and dispositional emotions in decision making: An ERP study. *Biological Psychology*, *123*, 126–135. doi:10.1016/j.biopsycho.2016.11.009
- Warren, C., Hyman, J., Seamans, J., & Holroyd, C. (2015). Feedback-related negativity observed in rodent anterior cingulate cortex. *Journal of Physiology-Paris*, *109*(1-3), 87–94. doi:10.1016/j.jphysparis.2014.08.008
- Watanabe, N., Sakagami, M., & Haruno, M. (2013). Reward prediction error signal enhanced by striatum–amygdala interaction explains the acceleration of probabilistic reward learning by emotion. *The Journal of Neuroscience*, *33*(10), 4487–4493. doi:10.1523/jneurosci.3400-12.2013
- Weinberg, A., & Hajcak, G. (2010). Beyond good and evil: The time-course of neural activity elicited by specific picture content. *Emotion*, *10*(6), 767. doi:10.1037/a0020242
- Weinberg, A., Luhmann, C., Bress, J., & Hajcak, G. (2012). Better late than never? The effect of feedback delay on ERP indices of reward processing. *Cognitive, Affective, & Behavioral Neuroscience*, *12*(4), 671–677. doi:10.3758/s13415-012-0104-z
- Weinberg, A., Perlman, G., Kotov, R., & Hajcak, G. (2016). Depression and reduced neural response to emotional images: Distinction from anxiety, and importance of symptom

- dimensions and age of onset. *Journal of Abnormal Psychology*, 125(1), 26.
doi:10.1037/abn0000118
- Weinberg, A., & Hajcak, G. (2011). Electrocortical evidence for vigilance-avoidance in Generalized Anxiety Disorder. *Psychophysiology*, 48(6), 842–851. doi:10.1111/j.1469-8986.2010.01149.x
- Weinberg, A. & Hajcak, G. (2011). Electrocortical evidence for vigilance-avoidance in Generalized Anxiety Disorder. doi:10.1111/j.1469-8986.2010.01149.x
- Weinfurt, K. P., Bryant, F. B., & Yarnold, P. R. (1994). The factor structure of the affect intensity measure: In search of a measurement model. *Journal of research in personality*, 28, 314–331.
- West, R. (2013). *Models of addiction* (pp. 1–161). Luxembourg: Publications Office of the European Union: European Monitoring Centre for Drugs and Drug Addiction.
- Whiteside, S., & Lynam, D. (2001). The Five Factor Model and impulsivity: using a structural model of personality to understand impulsivity. *Personality and Individual Differences*, 30(4), 669-689. doi:10.1016/s0191-8869(00)00064-7
- Whiteside, S., Lynam, D., Miller, J., & Reynolds, S. (2005). Validation of the UPPS impulsive behaviour scale: a four-factor model of impulsivity. *European Journal of Personality*, 19(7), 559–574. doi:10.1002/per.556
- Widiger, T. (1993). The DSM-III-R categorical personality disorder diagnoses: A critique and an alternative. *Psychological Inquiry*, 4(2), 75–90. doi:10.1207/s15327965pli0402_1
- Wikler, A., & Pescor, R.T. (1967). Classical conditioning of a morphine abstinence phenomenon, reinforcement of opioid-drinking behavior and "relapse" in morphine-addicted rats. *Psychopharmacologia*, 10(3), 255-284.

- Woicik, P., Stewart, S., Pihl, R., & Conrod, P. (2009). The substance use risk profile scale: A scale measuring traits linked to reinforcement-specific substance use profiles. *Addictive Behaviors, 34*(12), 1042–1055. doi:10.1016/j.addbeh.2009.07.001
- Xu, S., Martinez, L., Hoof, H., Eljuri, M., & Arciniegas, L. (2016). Fluctuating emotions: relating emotional variability and job satisfaction. *Journal of Applied Social Psychology, 46*(11), 617–626. doi:10.1111/jasp.12390
- Yeung, N., Holroyd, C., & Cohen, J. (2005). ERP Correlates of Feedback and Reward Processing in the Presence and Absence of Response Choice. *Cerebral Cortex, 15*(5), 535–544. doi:10.1093/cercor/bhh153
- Zheng, Y., & Liu, X. (2015). Blunted neural responses to monetary risk in high sensation seekers. *Neuropsychologia, 71*, 173–180. doi:10.1016/j.neuropsychologia.2015.04.002

Appendix A

In order to elucidate the relationship between substance use and questionnaires assessing individual differences, I examined correlations between overall substance use and the 13 subscales from the questionnaires (Table A1). Seven of the 13 subscales significantly correlated with overall substance use. These same subscales also comprised most of the factor loadings on the first factor of the PCA which I named reactivity. Most subscales from the AIM did not significantly correlate with substance use. This is in line with the results from the multiple regression analysis (see Table 3 in the Results section) in which factors (neuroticism and positivity) that heavily loaded on subscales from the AIM did not significantly predict substance use. These results support the factors identified by the PCA, as well as the relationship between the factors and substance use (i.e., individual differences in reactivity, but not intensity predict higher substance use).

	Overall Substance Use
<i>ALS - Anxiety/Depression</i>	.298**
<i>ALS - Depression/Elation</i>	.271*
<i>ALS - Anger</i>	0.161
<i>AIM - Negative Intensity</i>	.278*
<i>AIM - Negative Reactivity</i>	-0.022
<i>AIM - Positive Affectivity</i>	0.051
<i>AIM - Positive Intensity</i>	0.080
<i>UPPS-P Negative Urgency</i>	.406**
<i>UPPS - P Positive Urgency</i>	.348**
<i>SURPS - Impulsivity</i>	0.209
<i>SURPS - Anxiety Sensitivity</i>	-0.002
<i>SURPS - Hopelessness</i>	.229*
<i>SURPS - Sensation Seeking</i>	.274*

Table A1. Correlations between subscales from the ALS-SF, AIM, UPPS-P, and SURPS with overall substance use.

* $p < .05$, ** $p < .01$

I was interested in comparing the utility of the reactivity factor identified by the PCA in predicting substance use to the predictive power of the personality traits assessed by the SURPS, a questionnaire intended to assess personality traits associated with increased substance use (Woicik et al., 2009). To do this, I first regressed the PCA scores for the factor I named reactivity on the overall substance use score. I found reactivity significantly predicted increased substance use, $R^2 = .168$, $F(1,80) = 16.116$, $p < .001$. Next, I regressed the four personality dimensions assessed by the SURPS on substance use. The overall model also significantly predicted increased substance use, $R^2 = .137$, $F(4,77) = 3.062$, $p < .05$, but not as strongly as reactivity. Table A2 summarizes the correlation and regression results for the SURPS traits.

	<i>Hopelessness</i>	<i>Anxiety Sensitivity</i>	<i>Impulsivity</i>	<i>Sensation Seeking</i>
<i>Correlation</i>	.229*	-0.002	.209*	.274**
<i>B</i>	1.347	-0.47	0.957	1.391
<i>β</i>	0.202	-0.058	0.84	0.236

Table A2. Correlations with overall substance use, unstandardized (B) and standardized (β) regression coefficients.

* $p < .05$, ** $p < .01$

In order to explore further the relationship between the four factors identified in the current study and substance use, I examined correlations between the factors and self-reported use of specific substances (Table A3). Reactivity and sensation seeking were associated with increased use of cannabis, whereas reactivity was also associated with increased use of tobacco and amphetamines. Neuroticism and positivity appeared to be protective factors and were associated with lower use of cocaine, sedatives, and opioids. Notably, alcohol did not correlate significantly with any of the factors.

	Reactivity	Neuroticism	Positivity	Sensation Seeking
<i>Tobacco</i>	.277*			
<i>Cannabis</i>	.323**			.266*
<i>Amphetamine</i>	.376***			
<i>Cocaine</i>		-.231*		
<i>Sedatives</i>			-.421***	
<i>Opioids</i>			-.342**	
<i>Hallucinogens</i>				.243*

Table A3. PCA factors correlations with specific substance use scores.

* $p < .05$, ** $p < .01$, *** $p < .001$

Finally, I examined correlations between specific substance use scores and the four personality dimensions included in the SURPS (Table A4). In comparison to the relationships between specific substances and the PCA factors, none of the SURPS factors significantly correlated with tobacco use. This suggests that the relationship between tobacco and reactivity is likely due specifically to dimensions of affectivity reactivity that are not assessed by the SURPs (lability and urgency), rather than to impulsivity. Similar to the PCA factors, none of the SURPS traits significantly correlated with alcohol use.

	Hopelessness	Anxiety Sensitivity	Impulsivity	Sensation Seeking
<i>Cannabis</i>			.266*	.314**
<i>Amphetamine</i>	.287**		.336**	
<i>Cocaine</i>				
<i>Sedatives</i>	.304**			
<i>Opioids</i>	.285**			
<i>Hallucinogens</i>				.291**

Table A4. SURPS dimensions correlations with specific substance use scores.

* $p < .05$, ** $p < .01$