Neurocognitive predictors of self-reported reward responsivity and approach motivation in depression: a data-driven approach

Kean J. Hsu ^{1,2*}, Mary E. McNamara², Jason Shumake², Rochelle A. Stewart³, Jocelyn Labrada²,
Alexandra Alario⁴, Guadalupe D.S. Gonzalez², David M. Schnyer², Christopher G. Beevers²

¹Department of Psychiatry, Georgetown University Medical Center, Washington, DC

² Institute for Mental Health Research and Department of Psychology, University of Texas at Austin, Austin, TX

³Department of Psychology, Florida State University, Tallahassee, FL

⁴Interdisciplinary Graduate Program in Neuroscience, University of Iowa, Iowa City, IA

*Corresponding Author: Kean J. Hsu, Ph.D., Department of Psychiatry, Georgetown University Medical Center,
2115 Wisconsin Ave. NW, Suite 200, Washington, DC 20007 (kean.hsu@georgetown.edu)

RUNNING HEAD: COGNITIVE BIAS AND REWARD IN DEPRESSION

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Abstract

Background: Individual differences in reward-related processes, such as reward responsivity and approach motivation, appear to play a role in the nature and course of depression. Prior work suggests that cognitive biases for valenced information may contribute to these reward processes. Yet there is little work examining how biased attention, processing, and memory for positively- and negatively-valenced information may be associated with reward-related processes in samples with depression symptoms.

Methods: We used a data-driven, machine-learning (elastic net) approach to identify the best predictors of self-reported reward-related processes using multiple tasks of attention, processing, and memory for valenced information measured across behavioral, eye tracking, psychophysiological, and computational modeling approaches ($N = 202$). Participants were adults (ages 18 - 35) who ranged in depression symptom severity from mild to severe.

Results: Models predicted between 5.0-12.2% and 9.7-28.0% of held-out test sample variance in approach motivation and reward responsivity, respectively. Low self-referential processing of positively-valenced information was the most robust, albeit modest, predictor of low approach motivation and reward responsivity.

Conclusions: Self-referential processing of positive information is the strongest predictor of reward responsivity and approach motivation in a sample ranging from mild to severe depression symptom severity. Experiments are now needed to clarify the causal relationship between self-referential processing of positively-valenced information and reward processes in depression.

Keywords: behavioral activation system; attentional bias; cognitive processing; memory; depression; machine learning

1. Introduction

Impairments in reward processes, such as the loss of interest and pleasure in normally pleasurable activities (i.e., anhedonia), are a core symptom of depression (American Psychiatric Association, 2013; Pizzagalli, 2014). Accumulating evidence suggests that these reward-related deficits involve a variety of domains, including impaired reward responsivity and impaired approach motivation, each with distinct underlying neurobiological correlates (e.g., Cléry-Melin, Jollant, & Gorwood, 2019; Der-Avakian, Barnes, Markou, & Pizzagalli, 2015; Whitton, Treadway, & Pizzagalli, 2015). Deficits in these reward-related processes are not only apparent in depression but are also predictive of disorder development, persistence, and treatment response (e.g., Bress, Foti, Kotov, Klein, & Hajcak, 2013; Craske, Meuret, Ritz, Treanor, & Dour, 2016; McFarland, Shankman, Tenke, Bruder, & Klein, 2006; Vrieze et al., 2013). Moreover, blunted reward-related processes (as indexed by self-report measures of anhedonia) are associated with increased suicidal ideation and death by suicide even after controlling for other symptoms of depression (e.g., Ducasse et al., 2018; Fawcett et al., 1990; Hawes, Galynker, Barzilay, & Yaseen, 2018). These results suggest that individual differences in reward responsivity and approach motivation may play a role in the nature and course of depression. Identifying factors associated with individual differences in these reward-related deficits observed in depression can suggest translational targets for more personalized interventions addressing blunted reward processes (Forbes, 2009; Pizzagalli, 2014).

One important factor in depression that has yet to be studied in detail in relation to these reward-related impairments is cognition. Cognitive theories of depression highlight a number of cognitive processes that likely contribute to the development and persistence of reward deficits in depression. In particular, biases in the attention to, processing of, and memory for valenced information are hypothesized to serve as risk and maintenance factors for depression (Beck & Bredemeier, 2016; Disner, Beevers, Haigh, & Beck, 2011; Joormann & Michael Vanderlind, 2014). Studies with depressed individuals generally support these cognitive theories: depression is

associated with reduced gaze towards positive stimuli (see Armstrong & Olatunji, 2012) for a meta-analysis), hypoactivation of limbic and prefrontal areas for positive stimuli (e.g., Canli et al., 2005; Schaefer et al., 2006; Stuhmann et al., 2011), weaker positively biased self-referential processing, and poorer recall of positive information (e.g., Dillon, Dobbins, & Pizzagalli, 2014; Liu, Wang, Zhao, Ning, & Chan, 2012). Depressed individuals also show preferential gaze towards negative stimuli (Armstrong & Olatunji, 2012), enhanced processing of negative stimuli in the form of sustained pupil dilation and stronger event-related potentials commonly associated with processing (e.g., Ilardi, Atchley, Enloe, Kwasny, & Garratt, 2007; Siegle, Granholm, Ingram, & Matt, 2001), greater negatively biased self-referential processing (LeMoult & Gotlib, 2019), and facilitated recall of negative information (e.g., Gaddy & Ingram, 2014) compared to healthy controls. In short, cognitive processes that interact with positively- and negatively-valenced information appear to be perturbed in depression.

Yet the relationship between these cognitive biases and *reward deficits* in depression remains poorly understood. Prior work suggests that a key aspect of reward-related processes (Shechner et al., 2012; Winer, Samuel Winer, & Salem, 2016) and positive affect (Tamir & Robinson, 2007) is biased attention to positively-valenced information. As reviewed above, this cognitive bias seems to be lacking in depression. Depression is associated with impairments in reward-related processes so it may be that these cognitive biases for positively valenced information are contributing to deficits in reward-related processes. Yet, few studies have explicitly examined the relationship between individual differences in reward-related deficits and valenced cognition in depression, much less distinguished between different reward-related processes such as reward responsivity and approach motivation. Of the studies that have been conducted, most focus on a single cognitive processes such as memory (Damme et al., 2019; Liu et al., 2012; Olsen, Bjorkquist, Bodapati, Shankman, & Herbener, 2015), attention (Brailean, Koster, Hoorelbeke, & De Raedt, 2014), or self-referential processing (Kircanski, Mazur, & Gotlib, 2013), or psychophysiological processes believed to measure

these processes (e.g., the P300, N170, and LPC components of event-related potentials; Chen et al., 2014; Mallorquí, Padrao, & Rodriguez-Fornells, 2014) and do not study depression on a dimensional basis (i.e., only recruit on a categorical basis, by diagnostic group). These studies suggest that deficits in reward-related processes may be associated both with biases for positively-valenced information and negatively-valenced information in depressed individuals. However, no studies have examined how biased attention, processing, and memory for positively-valenced and negatively-valenced information collectively are associated with deficits in reward-related processes in samples expressing depression symptoms.

Thus, the current study attempts to identify the cognitive processes that best predict individual differences in reward responsivity and approach motivation in depression. To index cognition in this study, we drew upon a broad array of tasks that assess attention to, processing of, and memory for positively- and negatively-valenced information across multiple units of analysis. These tasks enabled us to measure attention, processing, and memory using a combination of behavioral, eye-tracking, psychophysiological, and computational modeling approaches. Given the large number of predictors available to operationalize attention, processing, and memory, we adopted a data-driven, machine learning approach to identify the best predictors of these reward processes across our sample. As the literature suggests biases for positively-valenced information and negatively-valenced information are both associated with deficits in reward-related processes across multiple units of analysis, we did not make specific predictions regarding which domain(s) or process(es) would be most predictive of reward functioning.

2. Materials and Methods

2.1 Procedure and participants

The current study is drawn from a larger, multi-modal study examining the contributions of genetic variability to cognitive vulnerability in depression (e.g., Beevers et al., 2019). We employed a

dimensional approach to studying depression in this study, recruiting a sample exhibiting a broad range of depression severity, from non-depressed to clinically depressed individuals, and deliberately oversampled the upper end of the depression severity continuum. Data were collected from 218 unrelated adults from the Austin, Texas community who visited the Mood Disorders Laboratory twice over two weeks to complete questionnaires, a clinical interview, and a battery of cognitive tasks (some of which were completed while electroencephalography data were being collected). Questionnaires and cognitive tasks were the same across both time points. Ten individuals were excluded because of other diagnoses that have known associations with aberrant reward processing (e.g. bipolar disorder). An additional six participants were excluded for missing 25% or more of their predictor data. This left a total sample size of 202 for the present study. Sample characteristics are provided in Table 1.

Table 1: Demographics and Clinical Characteristics of the Sample

Characteristic	Total (n = 202)
Age in years, mean (SD)	23.3 (4.9)
Female gender (%)	136 (67.3%)
Hispanic ethnicity (%)	63 (31.2%)
Caucasian (%)	200 (99.0%)
Single (%)	174 (86.1%)
Years in school (SD)	14.5 (2.4)
Private Health Insurance (%)	115 (56.9%)
Household Income (%)	
\$0 – \$24,999	77 (38.1%)
\$25,000 – \$74,999	65 (32.2%)
\$75,000 – \$100,000 +	60 (29.7%)
BDI-II (SD)	17.7 (11.5)

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BAS Drive	10.8 (2.7)
BAS Fun-Seeking	11.7 (2.6)
BAS Reward Responsiveness	16.9 (2.5)

Clinical characteristics	Percentage of Total Sample (n = 202)
Major Depressive Episode (current)	55 (27.2%)
Major Depressive Episode (lifetime)	121 (59.9%)
Panic disorder (current)	14 (6.9%)
Agoraphobia (current)	14 (6.9%)
Generalized Anxiety Disorder (current)	25 (12.4%)
Social Anxiety Disorder (current)	25 (12.4%)
Obsessive Compulsive Disorder (current)	13 (6.4%)
Post-Traumatic Stress Disorder (current)	9 (4.5%)
Alcohol Use Disorder (current)	28 (13.9%)
Substance Use Disorder (current)	28 (13.9%)

Individuals were eligible for the parent study based on the following inclusion criteria: 1) 18 to 35 years of age; 2) able to speak and read proficiently in English, and 3) either normal or corrected to normal vision. Due to the emphasis on examining genetic variability, we also only included individuals who were of European descent. The exclusion criteria were: 1) current use of steroidal or psychotropic medications; 2) serious medical conditions; 3) heavy tobacco use defined as 20 cigarettes per day or greater than 20 pack-years (Kamholz, 2004; World Health Organization, 2011); 4) score of two or higher on the drug subscale of the Psychiatric Diagnostic Screening Questionnaire (Zimmerman & Mattia, 2001); 5) a score of two or higher on the alcohol subscale of the Psychiatric Diagnostic Screening Questionnaire; 6) a score of one or higher on the psychosis subscale of

Psychiatric Diagnostic Screening Questionnaire; or 7) being in imminent danger to others or self, or any recent suicidal behavior (i.e., suicidal ideation at level 4 on the Columbia-Suicide Severity Rating Scale in the past two months, or any suicidal behavior in the past two months). The restricted age range adopted in the parent study was designed to minimize the impact of cognitive aging on the neurocognitive outcomes of interest.

2.2 Outcomes

Reward responsivity and approach motivation were measured using the Behavioral Inhibition System/Behavioral Approach System (BIS/BAS) Questionnaire (Carver & White, 1994). The BIS/BAS measured two motivational systems: activation, or approach towards desirable outcomes (the BAS scale) and avoidance of punishment or aversive outcomes (the BIS scale). Additionally, the questionnaire includes three BAS subscales: reward responsiveness, which measures sensitivity to reward and reward anticipation; drive, which measures one's motivation to pursue goals; and fun-seeking, reflecting the desire to spontaneously pursue *novel*, potentially rewarding activities. The BAS is a well-validated, reliable, and common self-report measure to assess reward responsivity, approach motivation, and anhedonia in previous studies (e.g., Der-Avakian et al., 2015; Gard, Kring, Gard, Horan, & Green, 2007; Liverant et al., 2014; Olino, McMakin, & Forbes, 2018; Rizvi, Pizzagalli, Sproule, & Kennedy, 2016). It also demonstrates convergent validity with behavioral and neural indices of reward-related process (e.g., DelDonno et al., 2015; Schreuders et al., 2018; Urošević, Collins, Muetzel, Lim, & Luciana, 2012). We ran three elastic-net regression models with each of the BAS subscales as an outcome.

2.3 Predictors

The models included 223 predictor variables, encompassing basic sociodemographic characteristics as well as attention, processing, and memory for positively- and negatively-valenced information (see Table 2). To establish the contribution of these cognitive processes above and

beyond depression severity, we included current (e.g., Time 1) depression severity as measured by the Beck Depression Inventory-II (Beck, Steer, & Brown, 1996) as a predictor, albeit with items associated with loss of interest or pleasure removed (c.f., Leventhal, Chasson, Tapia, Miller, & Pettit, 2006; Pizzagalli, Jahn, & O'Shea, 2005). We also examined these models without including depression severity or demographics as a predictor – the results are included in the Supplemental Materials. As the pattern of results remained the same, we present the results including current depression severity and demographics as predictors. Detailed descriptions of each task, including their psychometric properties, are provided in the Supplemental Materials.

Table 2
Model 1 predictors – Demographics, SRET predictors, Dot-probe reaction-time predictors, free-viewing task predictors
Demographics

• Gender	• Hispanic (yes/no)	• Never married (yes/no)
• Marital status	• Highest degree	• Financial support
• Private insurance	• Private insurance (yes/no)	

Depression severity

- Beck Depression Inventory – with loss of interest/pleasure items removed

SRET - Processing

• # of positive words endorsed	• # of negative words endorsed	• Negative word RT
• Positive word RT	• Drift rate for positive words	• Drift rate for negative words
• Relative starting point for positive words	• Relative starting point for negative words	
• Threshold separation	• Response time constant	• Difference in speed of response execution
• Inter-trial variability in relative starting point	• Inter-trial variability of drift	• Inter-trial variability of non-decisional components
• Drift-diffusion model fit	• SRET Time to complete	

SRET - Memory

• # of positive words recalled	• # of negative words recalled

<ul style="list-style-type: none">• # of self-relevant positive words recalled	<ul style="list-style-type: none">• # of self-relevant negative words recalled	
<i>Affective dot-probe task –Reaction-time outcomes</i>		
<ul style="list-style-type: none">• Trial-level bias score for happy faces• Mean trial level bias score when trial-level bias is toward happy faces• Trial-level bias score for sad faces• Mean trial level bias score when trial-level bias is toward sad faces• Extradecisional bias (derived from drift-diffusion modeling)	<ul style="list-style-type: none">• Number of correct probe responses for happy face trials• Mean trial level bias score when trial-level bias is away from happy faces• Number of correct probe responses for sad face trials• Mean trial level bias score when trial-level bias is away from sad faces	<ul style="list-style-type: none">• Percent of trials where trial-level bias is toward happy face (when presented happy)• Variability in trial-level bias scores for happy face trials• Percent of trials where trial-level bias is toward sad face (when presented sad)• Variability in trial-level bias scores for sad face trials
<i>Free-viewing task - Attention</i>		
<ul style="list-style-type: none">• Fraction of time viewing emotional ROIs – positive images• Fraction of time viewing emotional ROIs – positive images (late stage, 3000 ms onwards)	<ul style="list-style-type: none">• Fraction of time viewing emotional ROIs – negative images• Fraction of time viewing emotional ROIs – negative images (late stage, 3000 ms onwards)	
<i>Free-viewing task – Processing</i>		
<ul style="list-style-type: none">• Mean pupil dilation to neutral images• Peak pupil dilation to neutral images• Mean pupil dilation to neutral images (late stage, 3000 ms onwards)• Peak pupil dilation to neutral images (late stage, 3000 ms onwards)	<ul style="list-style-type: none">• Mean pupil dilation to positive images• Peak pupil dilation to positive images• Mean pupil dilation to positive images (late stage, 3000 ms onwards)• Peak pupil dilation to positive images (late stage, 3000 ms onwards)	<ul style="list-style-type: none">• Mean pupil dilation to negative images• Peak pupil dilation to negative images• Mean pupil dilation to negative images (late stage, 3000 ms onwards)• Peak pupil dilation to negative images (late stage, 3000 ms onwards)
Model 2 Predictors – <i>In addition</i> to Model 1 predictors, adding eye-tracking from dot-probe task, behavioral and ERP outcomes from the affective working memory task		
<i>Dot-probe task – Eye tracking outcomes</i>		
<ul style="list-style-type: none">• Gaze bias towards	<ul style="list-style-type: none">• Initial gaze bias	<ul style="list-style-type: none">• Final gaze bias

<p>happy stimuli</p> <ul style="list-style-type: none"> • Percent of gaze towards happy stimuli • Mean gaze away from happy stimuli • Gaze bias towards sad stimuli • Percent of gaze towards sad stimuli • Mean gaze away from sad stimuli 	<p>towards happy stimuli</p> <ul style="list-style-type: none"> • Percent of gaze in the center when presented happy stimuli • Variability in gaze bias for happy stimuli • Initial gaze bias towards sad stimuli • Percent of gaze in the center when presented sad stimuli • Variability in gaze bias for sad stimuli 	<p>towards happy stimuli</p> <ul style="list-style-type: none"> • Mean gaze towards happy stimuli • Within-person correlation between reaction-time and gaze bias scores for happy stimuli • Final gaze bias towards sad stimuli • Mean gaze towards sad stimuli • Within-person correlation between reaction-time and gaze bias scores for happy stimuli
<i>Affective working memory task – Processing</i>		
<ul style="list-style-type: none"> • Mean LPC amplitude for frontal electrodes when <u>encoding</u> stimuli – neutral probe correctly responded to • Mean LPC amplitude for frontal electrodes when <u>encoding</u> stimuli – neutral probe incorrectly responded to • Mean LPC amplitude for frontal electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean LPC amplitude for frontal electrodes when <u>encoding</u> stimuli – sad probe 	<ul style="list-style-type: none"> • Mean LPC amplitude for central electrodes when <u>encoding</u> stimuli – neutral probe correctly responded to • Mean LPC amplitude for central electrodes when <u>encoding</u> stimuli – neutral probe incorrectly responded to • Mean LPC amplitude for central electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean LPC amplitude for central electrodes when <u>encoding</u> 	<ul style="list-style-type: none"> • Mean LPC amplitude for parietal electrodes when <u>encoding</u> stimuli – neutral probe correctly responded to • Mean LPC amplitude for parietal electrodes when <u>encoding</u> stimuli – neutral probe incorrectly responded to • Mean LPC amplitude for parietal electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean LPC amplitude for parietal electrodes when <u>encoding</u>

correctly responded to	stimuli – sad probe correctly responded to	stimuli – sad probe correctly responded to
<ul style="list-style-type: none"> • Mean P100 amplitude for frontal electrodes when <u>encoding</u> stimuli – neutral probe correctly responded to • Mean P100 amplitude for frontal electrodes when <u>encoding</u> stimuli – neutral probe incorrectly responded to • Mean P100 amplitude for frontal electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean P100 amplitude for frontal electrodes when <u>encoding</u> stimuli – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean P100 amplitude for central electrodes when <u>encoding</u> stimuli – neutral probe correctly responded to • Mean P100 amplitude for central electrodes when <u>encoding</u> stimuli – neutral probe incorrectly responded to • Mean P100 amplitude for central electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean P100 amplitude for central electrodes when <u>encoding</u> stimuli – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean P100 amplitude for parietal electrodes when <u>encoding</u> stimuli – neutral probe correctly responded to • Mean P100 amplitude for parietal electrodes when <u>encoding</u> stimuli – neutral probe incorrectly responded to • Mean P100 amplitude for parietal electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean P100 amplitude for parietal electrodes when <u>encoding</u> stimuli – sad probe correctly responded to
<ul style="list-style-type: none"> • Mean N170 amplitude for left hemisphere electrodes when <u>encoding</u> stimuli – neutral probe correctly responded to • Mean N170 amplitude for left hemisphere electrodes when <u>encoding</u> stimuli – neutral probe incorrectly responded to • Mean N170 amplitude for left hemisphere electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean N170 amplitude for left hemisphere electrodes when <u>encoding</u> stimuli – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean N170 amplitude for right hemisphere electrodes when <u>encoding</u> stimuli – neutral probe correctly responded to • Mean N170 amplitude for right hemisphere electrodes when <u>encoding</u> stimuli – neutral probe incorrectly responded to • Mean N170 amplitude for right hemisphere electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean N170 amplitude for right hemisphere electrodes when <u>encoding</u> stimuli – sad probe correctly responded to 	
<ul style="list-style-type: none"> • Mean P300 	<ul style="list-style-type: none"> • Mean P300 	<ul style="list-style-type: none"> • Mean P300

amplitude for frontal electrodes when encoding stimuli – neutral probe correctly responded to

- Mean P300 amplitude for frontal electrodes when encoding stimuli – neutral probe incorrectly responded to
- Mean P300 amplitude for frontal electrodes when encoding stimuli – sad probe correctly responded to
- Mean P300 amplitude for frontal electrodes when encoding stimuli – sad probe correctly responded to
- Mean N400 amplitude for frontal electrodes when encoding stimuli – neutral probe correctly responded to
- Mean N400 amplitude for frontal electrodes when encoding stimuli – neutral probe incorrectly responded to
- Mean N400 amplitude for frontal electrodes when encoding stimuli – sad probe correctly responded to

amplitude for central electrodes when encoding stimuli – neutral probe correctly responded to

- Mean P300 amplitude for central electrodes when encoding stimuli – neutral probe incorrectly responded to
- Mean P300 amplitude for central electrodes when encoding stimuli – sad probe correctly responded to
- Mean P300 amplitude for central electrodes when encoding stimuli – sad probe correctly responded to
- Mean N400 amplitude for central electrodes when encoding stimuli – neutral probe correctly responded to
- Mean N400 amplitude for central electrodes when encoding stimuli – neutral probe incorrectly responded to
- Mean N400 amplitude for central electrodes when encoding stimuli – sad probe correctly responded to

amplitude for parietal electrodes when encoding stimuli – neutral probe correctly responded to

- Mean P300 amplitude for parietal electrodes when encoding stimuli – neutral probe incorrectly responded to
- Mean P300 amplitude for parietal electrodes when encoding stimuli – sad probe correctly responded to
- Mean P300 amplitude for parietal electrodes when encoding stimuli – sad probe correctly responded to
- Mean N400 amplitude for parietal electrodes when encoding stimuli – neutral probe correctly responded to
- Mean N400 amplitude for parietal electrodes when encoding stimuli – neutral probe incorrectly responded to
- Mean N400 amplitude for parietal electrodes when encoding stimuli – sad probe correctly responded to

<ul style="list-style-type: none"> • Mean N400 amplitude for frontal electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean LPP amplitude for frontal electrodes when <u>encoding</u> stimuli – neutral probe correctly responded to • Mean LPP amplitude for frontal electrodes when <u>encoding</u> stimuli – neutral probe incorrectly responded to • Mean LPP amplitude for frontal electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean LPP amplitude for frontal electrodes when <u>encoding</u> stimuli – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean N400 amplitude for central electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean LPP amplitude for central electrodes when <u>encoding</u> stimuli – neutral probe correctly responded to • Mean LPP amplitude for central electrodes when <u>encoding</u> stimuli – neutral probe incorrectly responded to • Mean LPP amplitude for central electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean LPP amplitude for central electrodes when <u>encoding</u> stimuli – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean N400 amplitude for parietal electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean LPP amplitude for parietal electrodes when <u>encoding</u> stimuli – neutral probe correctly responded to • Mean LPP amplitude for parietal electrodes when <u>encoding</u> stimuli – neutral probe incorrectly responded to • Mean LPP amplitude for parietal electrodes when <u>encoding</u> stimuli – sad probe correctly responded to • Mean LPP amplitude for parietal electrodes when <u>encoding</u> stimuli – sad probe correctly responded to
<i>Affective working memory task – Memory</i>		
<ul style="list-style-type: none"> • Neutral probe accuracy • Neutral probe – (other) Neutral face location error • Sad probe – (other) Sad face location error • Mean LPC amplitude for frontal electrodes when <u>responding</u> to probe – neutral 	<ul style="list-style-type: none"> • Sad probe accuracy • Neutral probe – Sad face location error • Sad probe – Neutral face location error • Mean LPC amplitude for central electrodes when <u>responding</u> to 	<ul style="list-style-type: none"> • Mean LPC amplitude for parietal electrodes when <u>responding</u> to

probe correctly responded to	probe – neutral probe correctly responded to	probe – neutral probe correctly responded to
<ul style="list-style-type: none"> • Mean LPC amplitude for frontal electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to 	<ul style="list-style-type: none"> • Mean LPC amplitude for central electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to 	<ul style="list-style-type: none"> • Mean LPC amplitude for parietal electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to
<ul style="list-style-type: none"> • Mean LPC amplitude for frontal electrodes when <u>responding</u> to probe – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean LPC amplitude for central electrodes when <u>responding</u> to probe – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean LPC amplitude for parietal electrodes when <u>responding</u> to probe – sad probe correctly responded to
<ul style="list-style-type: none"> • Mean LPC amplitude for frontal electrodes when <u>responding</u> to probe – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean LPC amplitude for central electrodes when <u>responding</u> to probe – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean LPC amplitude for parietal electrodes when <u>responding</u> to probe – sad probe correctly responded to
<ul style="list-style-type: none"> • Mean P100 amplitude for frontal electrodes when <u>responding</u> to probe – neutral probe correctly responded to 	<ul style="list-style-type: none"> • Mean P100 amplitude for central electrodes when <u>responding</u> to probe – neutral probe correctly responded to 	<ul style="list-style-type: none"> • Mean P100 amplitude for parietal electrodes when <u>responding</u> to probe – neutral probe correctly responded to
<ul style="list-style-type: none"> • Mean P100 amplitude for frontal electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to 	<ul style="list-style-type: none"> • Mean P100 amplitude for central electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to 	<ul style="list-style-type: none"> • Mean P100 amplitude for parietal electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to
<ul style="list-style-type: none"> • Mean P100 amplitude for frontal electrodes when <u>responding</u> to probe – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean P100 amplitude for central electrodes when <u>responding</u> to probe – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean P100 amplitude for parietal electrodes when <u>responding</u> to probe – sad probe correctly responded to
<ul style="list-style-type: none"> • Mean P100 amplitude for frontal electrodes when 	<ul style="list-style-type: none"> • Mean P100 amplitude for central electrodes 	<ul style="list-style-type: none"> • Mean P100 amplitude for parietal electrodes

<u>responding</u> to probe – sad probe correctly responded to	when <u>responding</u> to probe – sad probe correctly responded to	when <u>responding</u> to probe – sad probe correctly responded to
<ul style="list-style-type: none"> • Mean N170 amplitude for left hemisphere electrodes when <u>responding</u> stimuli – neutral probe correctly responded to • Mean N170 amplitude for left hemisphere electrodes when <u>responding</u> stimuli – neutral probe incorrectly responded to • Mean N170 amplitude for left hemisphere electrodes when <u>responding</u> stimuli – sad probe correctly responded to • Mean N170 amplitude for left hemisphere electrodes when <u>responding</u> stimuli – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean N170 amplitude for right hemisphere electrodes when <u>responding</u> stimuli – neutral probe correctly responded to • Mean N170 amplitude for right hemisphere electrodes when <u>responding</u> stimuli – neutral probe incorrectly responded to • Mean N170 amplitude for right hemisphere electrodes when <u>responding</u> stimuli – sad probe correctly responded to • Mean N170 amplitude for right hemisphere electrodes when <u>responding</u> stimuli – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean N170 amplitude for right hemisphere electrodes when <u>responding</u> stimuli – neutral probe correctly responded to • Mean N170 amplitude for right hemisphere electrodes when <u>responding</u> stimuli – neutral probe incorrectly responded to • Mean N170 amplitude for right hemisphere electrodes when <u>responding</u> stimuli – sad probe correctly responded to • Mean N170 amplitude for right hemisphere electrodes when <u>responding</u> stimuli – sad probe correctly responded to
<ul style="list-style-type: none"> • Mean N200 amplitude for frontal electrodes when <u>responding</u> to probe – neutral probe correctly responded to • Mean N200 amplitude for frontal electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to • Mean N200 amplitude for frontal electrodes when <u>responding</u> to probe – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean N200 amplitude for central electrodes when <u>responding</u> to probe – neutral probe correctly responded to • Mean N200 amplitude for central electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to • Mean N200 amplitude for central electrodes when <u>responding</u> to probe – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean N200 amplitude for parietal electrodes when <u>responding</u> to probe – neutral probe correctly responded to • Mean N200 amplitude for parietal electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to • Mean N200 amplitude for parietal electrodes when <u>responding</u> to probe – sad probe correctly responded to
<ul style="list-style-type: none"> • Mean N200 amplitude for frontal electrodes when <u>responding</u> to probe – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean N200 amplitude for central electrodes when <u>responding</u> to probe – sad probe correctly responded to 	<ul style="list-style-type: none"> • Mean N200 amplitude for parietal electrodes when <u>responding</u> to probe – sad probe correctly responded to

• Mean P300 amplitude for frontal electrodes when <u>responding</u> to probe – neutral probe correctly responded to	• Mean P300 amplitude for central electrodes when <u>responding</u> to probe – neutral probe correctly responded to	• Mean P300 amplitude for parietal electrodes when <u>responding</u> to probe – neutral probe correctly responded to
• Mean P300 amplitude for frontal electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to	• Mean P300 amplitude for central electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to	• Mean P300 amplitude for parietal electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to
• Mean P300 amplitude for frontal electrodes when <u>responding</u> to probe – sad probe correctly responded to	• Mean P300 amplitude for central electrodes when <u>responding</u> to probe – sad probe correctly responded to	• Mean P300 amplitude for parietal electrodes when <u>responding</u> to probe – sad probe correctly responded to
• Mean P300 amplitude for frontal electrodes when <u>responding</u> to probe – sad probe correctly responded to	• Mean P300 amplitude for central electrodes when <u>responding</u> to probe – sad probe correctly responded to	• Mean P300 amplitude for parietal electrodes when <u>responding</u> to probe – sad probe correctly responded to
• Mean N400 amplitude for frontal electrodes when <u>responding</u> to probe – neutral probe correctly responded to	• Mean N400 amplitude for central electrodes when <u>responding</u> to probe – neutral probe correctly responded to	• Mean N400 amplitude for parietal electrodes when <u>responding</u> to probe – neutral probe correctly responded to
• Mean N400 amplitude for frontal electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to	• Mean N400 amplitude for central electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to	• Mean N400 amplitude for parietal electrodes when <u>responding</u> to probe – neutral probe incorrectly responded to
• Mean N400 amplitude for frontal electrodes when <u>responding</u> to probe – sad probe correctly responded to	• Mean N400 amplitude for central electrodes when <u>responding</u> to probe – sad probe correctly responded to	• Mean N400 amplitude for parietal electrodes when <u>responding</u> to probe – sad probe correctly responded to

• Mean N400 amplitude for frontal electrodes when <u>responding</u> to probe – sad probe correctly responded to	• to Mean N400 amplitude for central electrodes when <u>responding</u> to probe – sad probe correctly responded to	• to Mean N400 amplitude for parietal electrodes when <u>responding</u> to probe – sad probe correctly responded to

2.3.1 Attention. Two tasks were used to assess attention to valenced information: the dot-probe task and a free-viewing task presenting complex emotional images. The dot-probe task presents two faces, one valenced and one non-valenced, for 1000 ms before the faces are replaced with a probe the participant responds to in the location of one of the faces. For the dot-probe, we used traditional mean bias scores, as well as a variety of outcomes that have been developed to address the poor psychometrics of the dot-probe task (c.f., McNally, 2018; Rodebaugh et al., 2016). These outcomes include gaze bias scores, dwell time, and trial-level bias scores (see Price et al., 2015; Zvielli, Bernstein, & Koster, 2014) along with computational modeling bias scores (based on drift-diffusion modeling; see Price, Brown, & Siegle, 2019) as measures of attention. As noted above, we also report the psychometric properties of these outcomes in our Supplemental Materials, which range from -.088 for initial gaze toward negative stimuli to .89 for variability in gaze bias for negative stimuli for split-half reliability. For the free-viewing task, we presented individual images from the International Affective Picture System (Lang, Bradley, & Cuthbert, 2005) for 6000 ms each. Images were evaluated by two independent coders for emotional regions of interest and consensus regions were identified for each image. The main attention outcomes for this task was mean proportion of time dwelling on emotional vs. non-emotional regions of interest across trials, as well as mean dwell time proportion for late-stage processing -- 3000 ms and onwards post-stimulus presentation.

2.3.2 Processing. Three tasks were used to assess the processing of valenced information: a free-viewing task involving complex images, the Self-Referential Encoding Task (SRET), and an affective working-memory task.

2.3.2.1 Psychophysiological indices of processing of complex images during free-viewing. For the free-viewing task, we used peak and mean pupil dilation (both total and late-stage processing -- 3000 ms and onwards post-stimulus presentation) to each image as a psychophysiological index of cognitive processing (see Graur & Siegle, 2013).

2.3.2.2 Self-referential processing. The SRET presents 26 positive and 26 negative words, one word at a time, and has participants rate whether the presented word is self-descriptive (Derry & Kuiper, 1981). For the SRET, we used number of positive and negative words endorsed and drift-diffusion modeling outcomes as measures of self-referential processing (Dainer-Best, Lee, Shumake, Yeager, & Beevers, 2018; Dainer-Best, Trujillo, Schnyer, & Beevers, 2017).

2.3.2.3 Psychophysiological indices of stimulus processing and encoding during a facial working memory task. For the affective working-memory task, four pseudo-randomly selected faces (2 sad expression and 2 neutral expression) placed in a clock-like arrangement were presented for 1500 ms. After a delay period of 1500 ms, a single face was presented (which was always one seen in the encoding screen) and participants were asked to indicate the location of the face during encoding. We examined several event-related potential (ERP) components believed to capture cognitive processes (e.g., P100, N170, P300) during the encoding phase of this task (e.g., Eimer, 2000; Rossion & Caharel, 2011).

2.3.3 Memory. Two tasks were used to assess memory processes for valenced information: the SRET and an affective working-memory task. For the SRET, following the rating of words participants complete a distractor task (a digit span task) and then are asked to freely recall as many words as possible for five minutes. We used number of positive and negative words endorsed as measures of learning and self-referent memory. For the affective working memory task, we used

accuracy and error types, as well as ERPs believed to capture cognitive processes (e.g., N200; P300; LPC) during the probe phase of the task (e.g., Hu, Pornpattananangkul, & Rosenfeld, 2013; Zhang, Wu, Kong, Weng, & Du, 2010) to index visual working memory.

2.4 Machine Learning Analyses

2.4.1 Learning Algorithms and Tuning Parameters

Unlike traditional data analytic approaches (e.g., linear regression), machine learning methods, such as elastic net regularized regression, can be used for variable selection problems when there are a large set of predictors that may be highly correlated with one another to identify the combination of variables that best predict an outcome of interest (Hastie, Tibshirani, & Wainwright, 2015). Elastic-net machine learning algorithms use both lasso and ridge regression penalties to prevent overfitting of the model. The elastic net regularization α parameter finds a compromise between the lasso penalty (sum of absolute values of all coefficients) and ridge penalty (sum of squared values of all coefficients) by weighting the proportion of ridge and lasso penalties. Cross-validation also tunes a second parameter, λ , which is the magnitude of the shrinkage penalty. For the current study, we made use of the *beset* package (<https://github.com/jashu>) developed in-house by co-author (JS). The *beset* wrapper tries over 100 possible values of λ (autogenerated by the package), as well as three values of α : 0.01 (weighting the ridge penalty more heavily and therefore including more variables, 0.99 (weighting the lasso penalty more heavily and including fewer variables), and 0.50 (equal weighting of both penalties). The parameter values are then chosen by the largest value that still remains within one standard error of the values that resulted in the minimum cross-validation error. The elastic net penalty determines model degrees of freedom, as opposed to the number of predictors, making it an attractive choice for identifying the best predictors from a large pool of options (Hastie et al., 2015).

2.4.2 Predictor Metrics and Cross-Validation

Predictive R^2 was used to evaluate model success. Predictive R^2 is the proportion of variance a given model is expected to explain in a new dataset (i.e. data that has not yet been “seen” by the model and was not used to train the algorithm). We used 10-fold cross-validation repeated 10 times to derive predictive R^2 . In each repetition of K-fold cross-validation, the data are split into K partitions (or folds). K-1 of the folds are used to train the algorithm, and then the final holdout data are used to test the predictive model. This process is then repeated, and predictive R^2 is derived from the average residual error of holdout prediction across the total number of repetitions (in our case, 10 repetitions).

Nested cross-validation was also conducted within each partition of training data at the first timepoint in order to determine the optimal values of the tuning parameters mentioned above. Most machine learning algorithms require tuning of several hyperparameters, which is typically derived by testing out hundreds of models with different hyperparameters and selecting those that perform best under cross-validation. Testing multiple models can result in overfitting, however (Ng, 1997). Limiting the number of hyperparameters being tested can reduce the number of models being tested. Further, using nested cross-validation can help obtain an unbiased estimate of test error (Varma & Simon, 2006) by embedding an additional 10-fold cross-validation procedure within the 90% of the data set aside for model training to select tuning parameters. We also report the standard error between cross-validation folds.

We then saved the optimal hyperparameters selected for by the cross-validation procedure at time point one and used those to test on “unseen” data from time point two (i.e., one week later). This allowed us to test whether the model honed at time point one also generalized to time point two, further assessing the robustness of prediction of unseen data. All predictors tested in the time point two model used data from time point two (e.g., current depression severity was depression severity measured at time point two).

2.4.3 Calculation of Variable Importance Scores

Variable importance was operationalized as the absolute magnitude of the standardized regression coefficient for each predictor (Wei, Lu, & Song, 2015). All analyses were implemented in R (version 3.5.3), and we utilized the *tidyverse* (Wickham, *n.d.*) for data manipulation. The *glmnet* package was used to run the elastic net models (Friedman, Hastie, & Tibshirani, 2010). We also used the *beset* package (<https://github.com/jashu/beset>) to run the models with cross-validation and produce variable importance plots.

2.4.4 Missing Data

Elastic net regularization requires data to be complete (i.e., no missing data), so missing data were imputed. A 25% exclusion rule was used prior to imputation; if any participant was missing more than 25% of their data, they were excluded, and if any predictor variable was missing for more than 25% of participants, it was dropped from the analyses. By using multiple models (see below), no variables were dropped in this manner, but 6 participants were excluded for a final total sample of $n = 202$. Additionally, three variables (white (yes/no), penalty (SRET), and method (SRET)) were subsetted out of the dataset prior to analysis because they had near-zero variance, indicating they all had nearly identical values. For example, because the parent project was reduced to people of European ancestry, all but 2 participants identified as white (they identified as white in the online screening but as “none of these options apply to me” in the demographics questionnaire). If nearly everyone has the same value for a given variable, it is unlikely to be a very useful predictor.

Following the exclusion of cases with large amounts of missing data, random forest imputation was performed utilizing the *missForest* package, which utilizes all other variables for each case to impute the missing value for a given variable. Outcome data were not included in the imputation, as using outcome data to impute prediction variables would later optimistically bias prediction.

2.4.5 Model comparison

If we use all available predictors, approximately 25% of participants are excluded due to our approach to handling missing data (see above). Consequently, to minimize the impact of missing data on our ability to identify cognitive predictors of reward-related processes and clarify the relative contribution (i.e., increase in explained variance) of each set of predictors, we tested two models. Our first test model was maximized for sample size (**Model 1**; $n = 202$) incorporated sociodemographic variables, current depression severity, all predictors from the self-referential encoding task, all predictors from the free-viewing task, and response time-related predictors from the dot-probe task (i.e., it *did not* include predictors based on eye-tracking from the dot-probe task, nor any behavioral or electrophysiological predictors from the affective working memory task). Our second test model was maximized for number of predictors available (i.e., all predictors; **Model 2**; $n = 158$). In order to compare the two models, we evaluated the second test model's predictive power relative to the first test model only for individuals who had electrophysiological data available -- that is, when comparing model 1 to model 2, we used the same cases across both models.

3. Results

3.1 Reward Responsivity

3.1.1 Model 1. Using a sample maximized for number of observations ($n = 202$).

The elastic net machine learning algorithm identified a model that predicted 14.2% of the variance in held-out test samples. This model consisted solely of number of positive words endorsed on the SRET, which was positively associated with reward responsivity. When predicting Time 2 data ($n = 199$) using the Time 1 model, it predicted 15% of the variance at this time point.

3.1.2 Model 2. Using a sample maximized for number of predictors available ($n = 158$).

The elastic net machine learning algorithm identified a model that predicted 9.7% of the variance in held-out test samples. This model was mainly comprised of several features from the SRET, several ERP components when presented with probes for neutral faces or encoding sad faces, and eye-tracking metrics towards positive stimuli from both attention tasks (see Table 3).

Table 3. Elastic Net Algorithm Model Results

Reward Responsivity		
Model 1 – Demographics, SRET predictors, dot-probe reaction time predictors, free-viewing task predictors		
Predictor	Standardized Regression Coefficient	Variance explained (in held-out test sample)
Time 1		14.2%
Number of positive words endorsed	0.19 (0.01)	
Time 2		15%
Number of positive words endorsed	0.18	
Model 2 – <u>In addition</u> to Model 1 predictors, adding eye-tracking from dot-probe task, behavioral and ERP outcomes from the affective working memory task		
Time 1		9.7%
Number of positive words endorsed	0.15 (0.02)	
Relative starting point for positive words	0.05 (0.02)	
Drift rate for positive words	0.05 (0.02)	
Mean amplitude of parietal electrodes for P300 ERP during encoding on trials with neutral probe correctly responded to	0.03 (0.02)	
Fraction of time attending to emotional regions of interest for positive images during late period (3000 ms onwards)	0.02 (0.01)	
Mean amplitude of parietal electrodes for LPC ERP during	-0.02 (0.01)	

encoding on trials with a sad probe incorrectly responded to	
Mean amplitude of left hemisphere electrodes for N170 during probe presentation on trials with a neutral probe correctly responded to	0.02 (0.01)
Mean gaze toward happy faces	0.02 (0.01)
Inter-trial variability of drift	0.01 (0.01)
Years of school	-0.01 (0.01)
Gaze bias for happy faces	0.01 (0.01)
Private insurance	0.01 (0.01)
Mean dilation to positive images	0.01 (0.01)
Inter-trial variability of non-decisional components	-0.01 (0.01)
Gender	-0.01 (0.00)
Mean amplitude for parietal electrodes for P100 during probe presentation on trials with a sad probe incorrectly responded to	0.01 (0.00)
Number of positive self-relevant words recalled	0.00 (0.00)
Never married	0.00 (0.00)
Extradecisional bias	0.00 (0.00)
Fraction of time attending to emotional regions of interest for positive images (full trial length)	
Time 2	28.0%
Relative starting point for positive words	0.16
Drift rate for positive words	0.14
Number of positive words endorsed	0.13
Mean amplitude of parietal electrodes for P300 ERP during encoding on trials with	0.09

neutral probe correctly responded to	
Mean amplitude of parietal electrodes for LPC ERP during encoding on trials with a sad probe incorrectly responded to	-0.07
Fraction of time attending to emotional regions of interest for positive images during late period (3000 ms onwards)	0.06
Mean amplitude of central electrodes for N200 ERP during probe presentation on trials with a sad probe responded correctly to	-0.06
Mean amplitude for left hemisphere electrodes for N170 ERP during probe presentation on trials with a neutral probe correctly responded to	0.06
Mean gaze toward happy faces	0.05
Inter-trial variability of drift	0.05
Years of school	-0.05
Mean amplitude for frontal electrodes for P100 during encoding of stimuli on trials with a neutral probe incorrectly responded to	0.05
Gaze bias for happy faces	0.04
Mean amplitude for parietal electrodes for P100 during probe presentation on trials with a sad probe incorrectly responded to	0.03
Variability in trial-level bias for happy faces	-0.03
Private insurance	0.02

Gender	-0.02
Inter-trial variability of non-decisional components	-0.02
Mean dilation to positive images	0.01
Never married	0.01
Number of positive self-relevant words recalled	0.01
Fraction of time attending to emotional regions of interest for positive images (full trial length)	0.01
Extradecisional bias	0.00
Mean amplitude of frontal electrodes for P100 ERP when encoding stimuli on trials with a sad probe correctly responded to	0.00
Drive	
<i>Model 1 – Demographics, SRET predictors, dot-probe reaction time predictors, free-viewing task predictors</i>	
Time 1	12.2%
Number of positive words endorsed	0.19 (0.01)
BDI (with loss of interest items removed)	-0.01 (0.01)
Time 2	12.0%
Number of positive words endorsed	0.19
<i>Model 2 – <u>In addition</u> to Model 1 predictors, adding eye-tracking from dot-probe task, behavioral and ERP outcomes from the affective working memory task</i>	
Time 1	6.0%
Number of positive words endorsed	0.11 (0.01)
Time 2	8.0%
Number of positive words endorsed	0.10
Fun Seeking	
<i>Model 1 – Demographics, SRET predictors, dot-probe reaction time predictors, free-viewing task predictors</i>	
Time 1	9.6%
Number of positive words endorsed	0.15 (0.01)

Time 2		10.0%
Number of positive words endorsed	0.16	
Model 2 – <i>In addition to Model 1 predictors, adding eye-tracking from dot-probe task, behavioral and ERP outcomes from the affective working memory task</i>		
Time 1		5.0%
Number of positive words endorsed	0.08 (0.01)	
Time 2		8.0%
Number of positive words endorsed	0.11	

Notes. SRET = Self-referential encoding task, BDI = Beck Depression Inventory – II, ERP = Event-related potential, LPC = Late positive component

When predicting Time 2 data using the Time 1 model ($n = 156$), predictors again included several features from the SRET, several ERP components when presented with probes for neutral faces or encoding sad faces from the affective working memory task, and eye-tracking metrics towards positive stimuli from both attention tasks (see Table 3). It predicted 28% of the variance at this time point.

When evaluating the model with the full predictor set (i.e., Model 2) to the model with a reduced predictor set (i.e., Model 1; with the same participants as Model 2, though), Model 2 showed a -1.6% change in predicted out-of-sample variance (95% confidence interval: -8.3% to 4%). This result suggests that adding behavioral, electrophysiological, and eye-tracking outcomes from an affective working memory task and dot-probe task as predictors of reward responsivity does not significantly increase the variance predicted in held-out test samples in the model with Time 1 data.

3.2 Drive

3.2.1 Model 1. Using a sample maximized for number of observations ($n = 201$).

One participant did not complete the entire subscale and was dropped from the analysis. The elastic net machine learning algorithm identified a model that predicted 12.2% of the variance in held-

out test samples. Number of positive words endorsed on the SRET was positively associated with drive and depression severity was negatively associated with drive in this model. When predicting Time 2 data (n = 200) using the Time 1 model, only number of positive words endorsed was kept from the Time 1 model. It predicted 12.0% of the variance at this time point.

3.2.2 Model 2. Using a sample maximized for number of predictors available (n = 158).

The elastic net machine learning algorithm identified a model that predicted 6.0% of the variance in held-out test samples. This model consisted solely of number of positive words endorsed on the SRET, which was positively associated with drive. When predicting Time 2 data (n = 157) using the Time 1 model, it predicted 8% of the variance at this time point.

When evaluating Model 2 to Model 1 (with the same participants as Model 2, though) at Time 1, Model 2 showed a -1.3% change in predicted out-of-sample variance (95% confidence interval: -3.1% to 0.3%). This result suggests that adding behavioral, electrophysiological, and eye-tracking outcomes from an affective working memory task and dot-probe task as predictors of drive does not significantly increase the variance predicted in held-out test samples in the model with Time 1 data.

3.3 Fun-seeking

3.3.1 Model 1. Using a sample maximized for number of observations (n = 200).

Two participants did not complete the entire subscale and were dropped from the analysis. The elastic net machine learning algorithm identified a model that predicted 9.6% of the variance in held-out test samples. Number of positive words endorsed on the SRET was positively associated with fun-seeking in this model. When predicting Time 2 data (n = 200) using the Time 1 model, it predicted 10% of the variance at this time point.

3.3.2 Model 2. Using a sample maximized for number of predictors available (n = 156).

Two participants did not complete the entire subscale at Time 1 and a separate individual was excluded for missing data at Time 2. They were dropped from those analyses. The elastic net machine learning algorithm identified a model that predicted 5.0% of the variance in held-out test

samples. This model consisted only of number of positive words endorsed on the SRET, which was positively associated with fun-seeking. When predicting Time 2 data ($n = 157$) using the Time 1 model, it predicted 8.0% of the variance at this time point.

When evaluating Model 2 to Model 1 (with the same participants as Model 2, though), Model 2 showed a -2.3% change in predicted out-of-sample variance (95% confidence interval: -3.9% to -0.8%). This result suggests that adding behavioral, electrophysiological, and eye-tracking outcomes from an affective working memory task and dot-probe task as predictors of fun-seeking does not significantly increase the variance predicted in held-out test samples in the model with Time 1 data.

4. Discussion

Dysfunction in reward-related processes are a core symptom of depression and play a role in the nature and course of the disorder. Impairments in these reward processes may also relate to biased attention, processing, and memory for valenced information, yet these potential connections have not been clearly and comprehensively examined to our knowledge. Our study sought to identify which cognitive processes were the best predictors of individual differences in reward-related impairments in a sample normally distributed for depression severity. We specifically employed an elastic net machine learning algorithm to identify and cross-validate optimal predictors for reward responsivity and approach motivation in a sample expressing a range of depression symptoms from outcomes derived from a range of behavioral tasks that index multiple aspects of cognition across behavioral and psychophysiological units of analysis.

Our results found that self-referential processing of positively-valenced information was the most robust predictor of reward responsivity, goal-oriented drive, and motivation for new rewards across all models. Greater endorsement of positively-valenced words was predictive of higher reward responsivity and approach motivation (i.e., drive and fun-seeking). Models including endorsement of positively-valenced words predicted 5-12% of out of sample variance for approach motivation and 10-

28% of out of sample variance for reward responsivity. This pattern of results held even when participants were assessed again, one week later. Our results also did not differ whether or not we included depression severity as a predictor, suggesting that these findings do not just express the relationship between neurocognitive variables and depression severity as captured by the BAS subscales and that these predictors are indeed associated with reward-related processes. Perhaps surprisingly, endorsement of positively-valenced words regarding the self was the *only* significant predictor for goal-oriented drive and motivation for new rewards across *both* time points. These findings suggest that self-referential processing of positively-valenced information is the cognitive process most clearly, albeit modestly, associated with approach motivation in individuals presenting with a wide range of depression severity.

To date, only one study has examined self-referential processing in relation to blunted reward-related processes in depression, in a sample of remitted depressed and healthy control individuals (Kircanski et al., 2013). Kircanski and colleagues found that reward responsivity was positively associated with number of positive words endorsed on the SRET only for remitted depressed individuals, not healthy control individuals. In addition, they found that reward responsivity was negatively associated with number of negative words endorsed only for remitted depressed individuals. Further, higher scores on the BAS-drive subscale was associated with the endorsement of more positive words, with remitted depressed individuals showing a stronger association between drive and positive words endorsed than healthy control individuals. The results of our study not only supports this association between positive self-referential processing and the reward processes of reward responsivity and approach motivation, but suggests that self-referential processing is the most robust cognitive predictor of reward responsivity and approach motivation.

Other cognitive processes, like attention and memory for valenced information, were less clearly associated with these processes in depression. Only reward responsivity, an index of reward anticipation and consumption, was associated with cognitive processes other than self-referential

processing. Notably, gaze towards positively-valenced stimuli in two different measures of attentional bias was associated with reward responsivity. Previous work using a behavioral (i.e., reaction-time based) dot-probe modified to examine biases to stimuli conditioned as rewarding found that, although biases to rewarding stimuli were not associated with subscales of the BAS, dysphoric individuals failed to develop a bias towards rewarding stimuli compared to control individuals (Brailean et al., 2014). These results suggest that gaze bias may be a more sensitive measure of reward responsivity than biases based on reaction-time tasks and could be associated with reward learning. Future studies incorporating specific measures of reward learning are needed, however.

Electrophysiological markers of stimulus processing (i.e., N170 and P300) during presentation of neutral face probes on correctly responded trials were also positively associated with reward responsivity. In addition, stimulus processing (i.e., LPC) during encoding of stimuli during trials where participants later responded incorrectly to sad faces was negatively associated with reward responsivity. Although these other cognitive processes predicted 10% of the variance of reward responsivity in our sample in held-out test samples at Time 1, their inclusion in the model did not result in significantly improved model performance relative to models that only included self-referential processing (i.e., number of positive words endorsed). Consequently, although cognitive biases for negative information have been associated with reward-related processes in the literature previously, our work suggests they may not be as strong of a predictor of individual differences as positively-valenced processes, especially self-referential processing of positive information.

It should be noted that in spite of a broad array of tasks assessing attention, processing, and memory for positively- and negatively-valenced information across multiple units of analysis, we were only able to explain a relatively small amount of variance in approach motivation (and to a lesser extent, reward responsivity). This may suggest that cognitive biases only contribute modestly to self-reported reward dysfunction, at least with how cognitive biases were measured in the current study. Relatedly, it was notable that the self-report metric on the SRET (number of endorsements) was

strongly associated with self-reported aspects of reward-related processes, whereas many of the task-based metrics were not. Shared method variance may partially account for our pattern of findings. However, not all self-report measures were strongly related to reward-related processes, which argues against shared method variance as the primary reason for the association with the SRET. Poor convergence between self-report and task-based measures is not uncommon (for further discussion see Dang et al., in press). Given this lack of convergence, it may be necessary to measure cognitive biases broadly in order to capture associations with depression-related phenomena, such as approach motivation and reward responsiveness. More generally, this lack of convergence underscores a greater need to attend to the psychometrics of non-self-report measures in studies that examine dimensional processes across multiple units of analysis (e.g., National Institute of Mental Health Research Domain Criteria). The lack of utility of many of the predictors might be attributed to their poor reliability rather than the relevance of the construct that they are meant to measure.

Clinically, our results suggest that improving self-referential processing might improve these reward-related processes in depressed individuals. One method for increasing positive self-referential processing is through positive imagery training (Dainer-Best, Shumake, & Beevers, 2018). This computerized intervention has been found to increase positive self-referential processing, as well as reduce depression severity and negative self-referential processing, over the span of two weeks. For individuals expressing pronounced deficits in these reward-related processes, positive imagery training may provide a targeted translational intervention. Interventions designed to increase positive affect and target anhedonia (e.g., Craske et al., 2019; Taylor, Lyubomirsky, & Stein, 2017) might also increase positive self-referential processing. Future studies ought to use experimental manipulation of self-referential processing to provide clinicians and researchers a clearer sense of the potential causal relationships between self-referential processing and reward-related dysfunction in depression.

Our study has a number of strengths, including a relatively large sample of individuals normally distributed on depression severity, a broad range of cognitive tasks incorporating behavioral, psychophysiological, and computational modeling approaches to index attention, processing, and memory for valenced information, cross-validation both within and across time points, and a data-analytic plan well-suited to leverage the large number of predictors available in this rich dataset. This study is a strong exemplar of the NIMH RDoC approach, incorporating multiple units of analysis to examine how cognitive processes are associated with dimensional measures of reward-related processes.

Our conclusions are tempered by a number of study limitations, however. First, given the restricted nature of this sample (i.e., of European descent, between ages 18 to 35, not currently taking psychotropic medications, denying elevated levels of alcohol or substance use or psychotic symptoms), it is unclear how much our results will generalize to more clinically complex and demographically diverse samples. In addition, we were only able to operationalize reward-related dysfunction by self-report, using the Behavioral Activation Scale. Although it exhibits convergent validity with behavioral measures of reward (e.g., DelDonno et al., 2015) and brain volume and activation in neural reward regions (e.g., nucleus accumbens; Schreuders et al., 2018; Urošević et al., 2012), this scale is not well-suited to clearly differentiating between reward anticipation and reward consumption, nor is it able to capture processes of reward learning and reward valuation. Future studies that employ additional measures of reward, including behavioral and neural units of analysis, to examine the links between self-referential processing (and other cognitive processes) and reward-related processes are merited. Finally, our study was cross-sectional in nature. Longitudinal and experimental studies are needed to follow up on these initial findings.

In spite of these limitations, our study is the first to examine how a broad range of cognitive processes are associated with reward-related dysfunction in depression. Our results suggest that self-referential processing of positive information is the best neurocognitive predictor of reward

responsivity and approach motivation in a sample of individuals expressing a broad range of depression severity. Experimental studies targeting self-referential processing or these reward processes will help to clarify the causal direction(s) of these relationships.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest to disclose.

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