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# Win, lose, or draw: Examining salience, reward memory, and depression with the reward positivity

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**Abstract**

The reward positivity (RewP) is a putative biomarker of depression. Careful control of stimulus properties and manipulation of both stimulus valence and salience could facilitate interpretation of the RewP. RewP interpretation could further be improved by investigating functional outcomes of a blunted RewP in depression, such as reduced memory for rewarding outcomes. This study sought to advance RewP interpretation first by advancing task design through use of neutral (i.e., draw) control trials and counterbalanced feedback stimuli. Second, we examined the RewP's association with memory and the impact of depression. Undergraduates completed self-report measures of depression and anhedonia prior to a modified doors task in which words were displayed in colored fonts that indicated win, loss, or draw feedback. Memory of the feedback associated with each word (i.e., source memory) was tested. Results showed that RewP response to wins was more positive than to losses, which was more positive than to draws. The RewP was not associated with depression or anhedonia. The low depression group showed a source memory advantage for win words, but the high depression group did not. Source memory showed small relations to the RewP, but these did not survive Bonferroni correction. Results suggest the RewP is sensitive to salience and highlight challenges in detecting an association between the RewP and depression in modified doors tasks. Findings indicate that depression is related to dysfunctional source memory for reward but not loss and that future research should probe the possible associations between the RewP and memory in depression.

**KEYWORDS**

depression, doors task, EEG, memory, reward positivity, salience

## 1 | INTRODUCTION

Over the past decade, researchers have studied an event-related potential (ERP) known as the reward positivity (RewP) as a possible neural biomarker of low reward responsiveness in depression (Proudfit, 2015). The RewP typically shows small negative correlations with self-reported depression (Belden et al., 2016; Bress et al., 2012; Brush et al., 2018; Foti & Hajcak, 2009) and is blunted in individuals with major depressive disorder (MDD; e.g., Brush et al., 2018; Foti et al., 2014; Klawohn et al., 2020). Low RewP amplitudes are also associated with anhedonia (i.e., reduced pleasure in activities; Cooper et al., 2014; Liu

[Correction added on October 17, 2021 after first online publication: Figure 2 has been updated.]

  

et al., 2014; Parvaz et al., 2016). The practical significance of the RewP is evident through studies showing that the RewP has predicted future depression (Bress et al., 2013, 2015; Hausman et al., 2018; Nelson et al., 2016) and depression treatment response (Barch et al., 2020; Burkhouse et al., 2016, 2018). However, the precise interpretation of the RewP has been a matter of uncertainty and studies have not examined the connection between the RewP and reward-related memory deficits, which are found in individuals with MDD (e.g., Lewis et al., 2017; Matt et al., 1992). Investigating these issues may improve understanding of the RewP and its clinical utility.

The RewP is commonly operationalized as the difference in ERP response to receiving rewards compared to losses (e.g., winning vs. losing money). Researchers have endeavored to understand whether this difference in ERP response, and thus the RewP, is driven by stimulus valence (i.e., whether the stimulus is rewarding vs. aversive) or stimulus salience (i.e., the importance of the stimulus regardless of whether it is rewarding or aversive). The perspective that the RewP responds to valence corresponds with the prevalent view that the RewP primarily responds to reward rather than loss (Proudfit, 2015). This view is supported by studies that suggest that the blunting of the RewP in people with MDD is a due to blunting of the ERP response to reward, not loss (Brush et al., 2018; Klawohn et al., 2020; Liu et al., 2014) and others that report no significant difference between ERP responses to loss and neutral trials (Holroyd et al., 2004, 2006; Kujawa et al., 2013). Neuroimaging data suggest that the RewP is associated with reward-sensitive brain structures, such as the striatum and medial prefrontal cortex (Becker et al., 2014; Carlson et al., 2015; Foti et al., 2011; Martin et al., 2009).

In contrast to the valence interpretation of the RewP, the salience interpretation argues that the RewP responds to all salient stimuli, whether they be reward or loss. Some studies that manipulate salience and valence have found support for the salience interpretation by showing a RewP-like response to both rewarding and aversive stimuli (e.g., Hird et al., 2018; Soder & Potts, 2018; Talmi et al., 2013). However, similar studies have also supported the valence interpretation (e.g., Heydari & Holroyd, 2016; Mulligan & Hajcak, 2018). A meta-analysis suggested that the RewP is modulated by valence and salience (Sambrook & Goslin, 2015). This may be due to underlying components of the RewP that overlap in time but respond uniquely to reward or loss, as suggested by studies that use principal component analysis (PCA) and time-frequency data (e.g., Foti et al., 2015; Rawls & Lamm, 2021; Rawls et al., 2020; Sambrook & Goslin, 2016). The uncertain impact of salience and valence on the RewP creates ambiguity in the interpretation of the typical RewP tasks used to examine depression, which only examine the effect of valence. Tasks that incorporate salience and valence could better define the depression-related deficit that the RewP indexes. Such work may better characterize the RewP's place in the National Institute of Mental Health's Research Domain Criteria, including the Positive Valence System, Negative Valence System, or both (National Institute of Mental Health [NIMH], 2011a; National Institute of Mental Health [NIMH], 2011b).

RewP studies on depression commonly use the doors task, in which participants win or lose money on each trial after selecting one of two doors (Proudfit, 2015). Adding a neutral condition to the doors task would act as a control for the brain's response to merely receiving feedback and provide insight into valence *and* salience, as loss trials have a negative valence and positive salience when compared to neutral trials. Although previous studies that have compared win, loss, and neutral trials have found no difference between loss and neutral trials, these studies may have been limited by their small samples ($N = 10$ to 23; Holroyd et al., 2004; Holroyd et al., 2006). Indeed, four experiments by Holroyd and colleagues (2006) indicated visually noticeable, but not significant, differences between loss and neutral trials. Examining these effects in a larger sample is needed to know whether ERP responses to loss and neutral trials differ. The doors task could be further improved by counterbalancing the physical characteristics of feedback stimuli, which are typically green up arrows and red down arrows. Such counterbalancing would increase confidence that effects can be attributed to the psychological meaning of the stimuli. Evolving the doors task through incorporation of neutral trials and counterbalanced stimuli may enable researchers to draw more precise interpretations of the RewP from this task.

Additional modifications to the doors task may provide insight into whether the RewP is related to impaired memory processes involved in depression and assess potential outcomes of a blunted RewP. Individuals with depression tend to have poorer memory for positive experiences and stimuli compared to those without depression (e.g., Burt et al., 1995; Dainer-Best et al., 2018; Gotlib et al., 2011; Gotlib et al., 2004; McDowall, 1984; Young et al., 2012), which theories propose helps initiate or maintains depression (Disner et al., 2011; Lemoult & Gotlib, 2019). Neuroimaging research shows that reward networks in the brain are involved in successful reward-related memory performance (e.g., Adcock et al., 2006; Wolosin et al., 2012). One neuroimaging study found that neural reward response was associated with reward-related memory in healthy controls, but they were not associated in people with MDD (Dillon et al., 2014). Importantly, a larger RewP during stimulus encoding has been linked to better recognition memory of positive stimuli (Höltje & Mecklinger, 2018). As such, the RewP may be a plausible

indicator of the reduced impact of neural reward processing on memory encoding in people with depression, but this is yet to be tested.

Research that improves our understanding of the RewP and how to interpret its connection to depression is necessary in light of some evidence that raises questions about the RewP being a depression biomarker. In meta-analyses, overall effect sizes of the RewP's association with depression were nonsignificant (Moran et al., 2017) or small to medium (Cohen's *d*s = 0.38 to 0.48; Clayson et al., 2020; Keren et al., 2018). The effect of depression on the RewP was also shown to depend on younger age (Keren et al., 2018) or using a guessing task, such as the doors task (Moran et al., 2017). Most recently, a meta-analysis found evidence of possible publication bias and concluded there was minimal support for the RewP as a biomarker of depression (Clayson et al., 2020). To improve the literature, researchers suggest analyzing depression continuously (Berry et al., 2019; Clayson et al., 2020) and using larger samples (Clayson et al., 2020). Further, time-frequency analysis may uncover depression-related differences not evident in the time domain. Specifically, depression has been associated with lower delta power in response to reward (Foti et al., 2015; Nelson et al., 2018) and greater theta power in response to loss (Webb et al., 2017), or both (Jin et al., 2019) in the RewP time window.

The current study aimed to clarify the RewP's relation to depression by modifying the doors task and assessing reward-related memory performance. First, in addition to monetary win and loss trials, we added draw (i.e., neutral) trials to the doors task. Second, we counterbalanced feedback stimuli across participants by using words in colored font instead of green up/red down arrows for feedback. Third, we presented emotionally neutral words during feedback on each trial and used these words later to test participants' source memory for feedback value. We used a larger sample size than is typical of RewP studies and examined depression both continuously and between groups, in addition to anhedonia. PCA and time-frequency analysis were applied along with ERP time-domain analyses.

It was hypothesized that the ERP response to win in the RewP time window would be more positive than to both loss and draw. We also compared ERP responses to loss versus draw. We hypothesized that higher depression severity, high depression group, and higher anhedonia severity would be associated with a smaller difference between the ERP responses to win versus both loss and draw. Depression was hypothesized to be related to lower delta power and greater theta power within the RewP time window. Source memory for win words was expected to be greater than for loss and draw words, but only for those without elevated depression or anhedonia. Better source memory for win, loss, and draw words was hypothesized to relate to a more positive corresponding ERP response, but this relation was expected to be stronger for people without elevated depression.

## 2 | METHOD

### 2.1 | Participants

The final sample consisted of 125 undergraduate students from a large southeastern university who were recruited via an online research system. Participants received research credit and $11 for their participation. Participants did not know how much money they would earn until after they completed the study task and were told the amount would be based on their performance. The final sample was determined after excluding data for 20 participants (13.6%) due to poor electroencephalography (EEG) data quality and for two participants (1.4%) due to data collection errors. Participants had a mean age of 21.9 years ($SD = 5.71$) and were predominantly women ($n = 90$; 72.0%). Participants were racially diverse, with the largest proportions identifying as White ($n = 60$; 48.0%) or Black ($n = 24$; 19.2%). See Table 1 for additional demographic information.

Participants with a Beck Depression Inventory-II (BDI-II) score greater than 17 ($n = 30$) were categorized into the high depression group, whereas those scoring less than 10 ($n = 61$) were categorized into the low depression group. A middle group with BDI-II scores from 10 to 17 ($n = 34$) were used only in continuous data analyses. These BDI-II cutoffs were based on previous research with college students that optimized the sensitivity and specificity of meeting or not meeting diagnostic criteria for a depressive disorder (Shean & Baldwin, 2008).

### 2.2 | Measures

#### 2.2.1 | Depression

The Beck Depression Inventory—Second Edition (BDI-II; Beck et al., 1996) was used to measure depression severity. On the BDI-II, individuals rate the frequency or intensity of 21 depression symptoms over the previous two weeks. Response options range from 0 (not symptomatic [e.g., *I do not feel sad*]) to 3 (most symptomatic [e.g., *I am so sad or unhappy that I can't stand it*]), such that higher scores indicate greater depression severity. Convergent validity (Storch et al., 2004) and test-retest reliability (Wang & Gorenstein, 2013) of the BDI-II have been demonstrated in undergraduate

**TABLE 1** Demographics and group comparisons

| | Total | Low depression | High depression | | | |
|---|---|---|---|---|---|---|
| | *N* = 125 | *n* = 61 | *n* = 30 | | | |
| **Variable** | | *M* (*SD*) | *M* (*SD*) | *t* | *df* | *p* |
| Age (years) | 21.9 (5.71) | 22.51 (6.18) | 21.50 (5.48) | 0.76 | 89 | .45 |
| BDI-II | 11.59 (8.84) | 4.67 (2.88) | 25.03 (4.93) | 20.93 | 89 | <.001 |
| SHAPS | 22.11 (5.93) | 19.89 (4.32) | 26.57 (7.24) | 4.66 | 89 | <.001 |
| | | *n* (%) | *n* (%) | $\chi^2$ | *df* | *p* |
| Gender | | | | 4.04 | 2 | .11 |
| Woman | 90 (72.0%) | 40 (65.6%) | 25 (83.3%) | | | |
| Man | 33 (26.4%) | 20 (32.8%) | 4 (13.3%) | | | |
| Transgender | 2 (1.6%) | 1 (1.6%) | 1 (3.3%) | | | |
| Race | | | | 3.37 | 7 | .85 |
| White | 60 (48.0%) | 30 (49.2%) | 13 (43.3%) | | | |
| Black | 24 (19.2%) | 14 (23.0%) | 6 (20.0%) | | | |
| Latinx | 11 (8.8%) | 4 (6.6%) | 3 (10.0%) | | | |
| South Asian | 3 (2.4%) | 2 (3.3%) | 1 (3.3%) | | | |
| East Asian | 6 (4.8%) | 1 (1.6%) | 1 (3.3%) | | | |
| Middle Eastern | 1 (0.8%) | 1 (1.6%) | 0 (0%) | | | |
| Pacific Islander | 1 (0.0%) | 0 (0%) | 1 (3.3%) | | | |
| Multiracial | 19 (15.2%) | 9 (14.8%) | 5 (16.7%) | | | |
| Class | | | | 4.26 | 4 | .37 |
| Freshman | 55 (44.0%) | 26 (42.6%) | 14 (46.7%) | | | |
| Sophomore | 21 (16.8%) | 7 (11.5%) | 6 (20.0%) | | | |
| Junior | 20 (16.0%) | 9 (14.8%) | 6 (20.0%) | | | |
| Senior | 26 (20.8%) | 17 (27.9%) | 4 (13.3%) | | | |
| Graduate | 2 (1.6%) | 2 (3.3%) | 0 (0.0%) | | | |
| Non-degree | 1 (0.8%) | 0 (0.0%) | 0 (0.0%) | | | |

*Note:* The *t*-tests and $\chi^2$ tests compare the low and high depression groups. Total includes participants in the middle BDI-II group.

Abbreviations: BDI-II, Beck Depression Inventory-II; SHAPS, Snaith-Hamilton Pleasure Scale.

students. Internal consistency in the current sample was excellent (Cronbach's $\alpha = 0.91$).

### 2.2.2 | Anhedonia

The Snaith-Hamilton Pleasure Scale (SHAPS; Snaith et al., 1995) is a 14-item questionnaire used to measure consummatory anhedonia. Individuals indicate the extent to which they would have experienced pleasure if they had engaged in particular activities over the previous few days (e.g., *I would enjoy my favorite television or radio program*). Items are scored as 1 = *Strongly agree*, 2 = *Agree*, 3 = *Disagree*, and 4 = *Strongly disagree*, such that higher scores indicate greater anhedonia. The SHAPS has shown evidence of convergent validity and test-retest reliability when used with undergraduate students (Franken et al., 2007). Internal consistency in the current sample was good (Cronbach's $\alpha = 0.86$).

## 2.3 | Study tasks

### 2.3.1 | Modified doors task

The doors task (Proudfit, 2015) was modified. The trial sequence and feedback dollar amounts of the original doors task were not changed, but a third door was added, as were draw feedback trials. Instead of green upward arrows and red downward arrows, counterbalanced colored words were used for feedback. Participants completed training trials in which they repeatedly

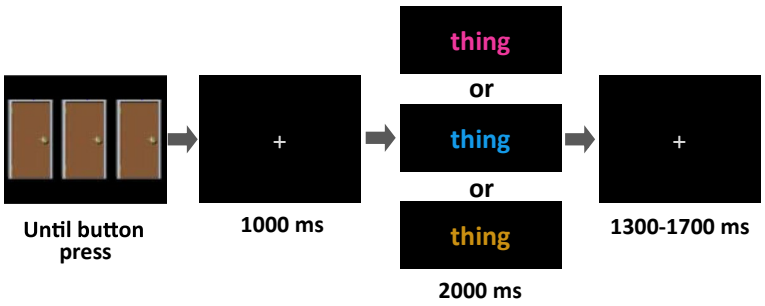


**FIGURE 1** One trial sequence in the modified doors task with the three possible stimulus values (i.e., colors) displayed. Participants made a button press to select one of three doors, which was followed by a fixation cross. A unique word appeared on the screen in one of three colors, which indicated whether the participant won (+$0.50), lost (−$0.25), or drew (±$0.00) on that trial. The trial ended with another fixation cross

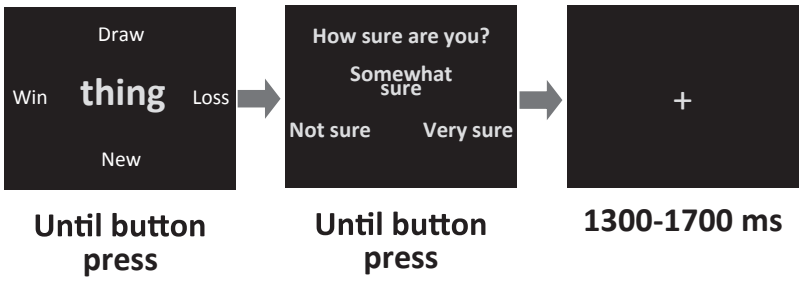


**FIGURE 2** One trial sequence of the source memory task. Participants made a button press to select whether the word displayed was associated with win, loss, draw, or was a new word. They next indicated their confidence in their selection. The trial ended with a fixation cross

demonstrated comprehension of the meaning of each color without committing errors. For the doors task, participants completed trials in which they viewed three identical doors on a computer screen and pressed a button (left, down, or right arrow on the keyboard) to choose one door to open (see Figure 1). Following this choice, the doors disappeared to show a fixation cross in the center of the screen. After 1,000 ms, the fixation cross was replaced by an emotionally neutral word written in one of three colors in the center of the screen. The color of the word indicated whether the choice of door resulted in a win (+$0.50), loss (−$0.25), or draw (±$0.00).[1] The word appeared on the screen for 2,000 ms, then the trial ended with a fixation cross on the screen for a randomized interval between 1,300 and 1,700 ms. A unique word was used in each trial so that memory of the words could be tested in the subsequent surprise memory task. There were 40 win, loss, and draw trials each for a total of 120 trials. The words were presented in three sets to allow for two 20 s breaks, and word order was randomized within each set. During each break, participants were reminded of the meaning of each color and told how much money they had earned up to that point. To prevent primacy and recency effects on memory performance (Kahana, 1996; Murdock, 1962), 12 additional trials (six at the beginning of the task and six at the end) were included in the task but excluded from memory and ERP analyses, in line with previous word memory studies (e.g., Glanzer et al., 2004; Slotnick et al., 2000; Van Vugt et al., 2012). After finishing all trials, participants completed a manipulation check in which they were tested on the previously learned meaning associated with each word color. All participants performed perfectly on this manipulation check.

### 2.3.2 | Source memory task

Immediately following the manipulation check, participants counted backwards from a three-digit number for 30 s to prevent rehearsal of the doors task words. After a two-min break, they were informed about the memory task in which all words from the doors task, along with 40 new words, were shown one-at-a-time in a random order (see Figure 2). Each of the 160 trials began a word

[1]The magnitude of win and loss trials was consistent with the amounts used in previous doors task studies (Proudfit, 2015). These amounts were originally chosen based on research by Tversky and Kahneman (1992), which shows that the experience of losing is twice as subjectively negative as winning is subjectively positive.

in white text in the center of the screen with four response options—"Win," "Loss," "Draw," and "New"—around the word (i.e., above, below, left, or right). The location of the options were counterbalanced across participants. Using a button press, participants selected the value (win, loss, or draw) they believed was associated with the word during the doors task or indicated that the word was new. Next, participants indicated their confidence in their selection as "Not sure," "Somewhat sure," or "Very sure." All trials, regardless of confidence rating, were used in analyses. Prior to the appearance of the next word, a fixation cross appeared in the center of the computer screen for a randomized interval between 1,300 and 1,700 ms.

## 2.4 | Task stimuli

Each word appeared in the same color for all participants, but the values that participants learned to associate with the colors were counterbalanced across participants. As such, counterbalancing controlled for the effect of color and word on ERP response. Colors had identical luminance (i.e., 60%) and saturation (i.e., 84%) to further control for visual effects on the ERP. The colors (pink [RGB = 238, 55, 155], blue [20, 154, 232], and orange [202, 144, 15]) were chosen to maximize ease of discrimination and suitability for people with color deficiency (see Wong, 2011). Training trials confirmed that all participants discriminated the colors from each other. Published databases (Brysbaert & New, 2009; Brysbaert et al., 2014; Warriner et al., 2013) were used to select words that had neutral valence and low arousal ratings and were highly common and concrete. Words were randomly assigned to one of three word lists (one for each color), which are provided in the Supplementary Materials. One-way ANOVAs showed that the three word lists did not differ on any of the characteristics (i.e., valence, arousal, commonness, concreteness) or on number of syllables, $F(3, 156) < 1.23$ and $p > .30$ for all characteristics.

## 2.5 | Procedure

Study procedures received approval from the Institutional Review Board. Participants first provided informed consent and then completed a battery of self-report questionnaires including the BDI-II and the SHAPS. Next, researchers applied the EEG cap and electrodes. They next were seated 70 cm from a high definition Dell computer monitor with a 60 Hz refresh rate, on which they completed the modified doors task. They then completed the 30-s counting task and manipulation check, followed by the source memory task. Participants were debriefed and paid $11 in cash.

## 2.6 | Electrophysiological data

### 2.6.1 | Data recording and pre-processing

EEG data were collected at a sampling rate of 1,024 Hz on a BioSemi ActiveTwo system with 33 sintered Ag/AgCl active EEG electrodes, which were positioned based on the 10/20 system. Two more electrodes, CMS (common mode sense) and DRL (driven right leg), were located on either side of Cz, with CMS serving as the online reference and CMS/DRL creating a feedback loop to ground the average potential of the participant. Electrooculogram (EOG) data measured vertical and horizontal eye movement with an electrode placed 1 cm lateral to the outer canthus of each eye and an electrode below the center of the left eye. Data were recorded with no online high-pass filter (i.e., DC-coupled) and with an online low-pass anti-aliasing filter with a 3dB/octave roll-off at one fifth the sampling rate. Electrophysiological data were processed in MATLAB (version R2019a) using EEGLAB (version 14; Delorme & Makeig, 2004) and ERPLAB (version 7.0.0; Lopez-Calderon & Luck, 2014). Offline, data were filtered using a Butterworth IIR (2nd order) high-pass filter with a cut-off of 0.1 Hz and a 12 dB/octave roll-off. The average of the two mastoid electrodes was used as a reference. Data were segmented for each trial into epochs from 400 ms before feedback to 1,000 ms after feedback, and −200 to 0 ms served as the pre-stimulus baseline period. Independent component analysis (Makeig et al., 1996) was used to correct for ocular artifacts (i.e., eye-blinks and saccades) in the EEG data by visually screening components for temporal and spatial features of such artifacts. Except for electrodes used in analyses (i.e., FCz, Cz, and Pz), electrodes were interpolated using spherical spline interpolation if the electrode recording was poor as determined by visual inspection, such that 1–3 electrodes were interpolated for 21% of participants. Automated ERPLAB artifact detection routines with a moving window peak-to-peak algorithm rejected trials with extreme values (±100 μV at FCz and ±200 μV at all other channels) and blocking (<0.1 μV change within 100 ms) or if they contained blinks or saccades within 200 ms of stimulus onset. Following visual inspection to verify optimal performance of artifact rejection, participants with more than 25% of trials rejected for any of the three stimulus types (win, loss, draw) were excluded from analysis. The participants included in analyses had a minimum of 30 and maximum of 40 trials for each condition, with means of 37.03 ($SD = 2.52$), 36.57 ($SD = 2.89$), and 37.05 ($SD = 2.69$) trials for win, loss, and draw conditions, respectively.

### 2.6.2 | Time domain processing

Separate feedback-locked ERPs were created for each trial type in ERPLAB. The primary dependent variable (henceforth referred to as *ERP response*) was the mean ERP amplitude during the 250–350 ms after feedback at the FCz electrode, the electrode at which the RewP is maximal and reliable in the doors task (Brush et al., 2018; Levinson et al., 2017; Proudfit, 2015). As previous research has also used PCA to operationalize the RewP, a two-step PCA was conducted using the ERP PCA Toolkit (version 2.90; Dien, 2010). For both steps (spatial and temporal), we used Horn's parallel analysis to select the number of components to extract. The resulting principal components were rescaled to microvolts (Dien, 2012), and factors putatively corresponding to the RewP were screened and selected based on scalp location, temporal profile, and task modulation. ERP response data quality was summarized using the root mean square of the standardized measurement error (RMS[*SME*]; see Luck et al., 2021). As recommended by Luck and colleagues, RMS(*SME*) was compared to the standard deviation of ERP response, wherein a "much smaller" RMS(*SME*) compared to the standard deviation "would indicate that the observed differences across individual participants are mainly driven by true individual differences, with relatively little impact of measurement error" (Luck et al., 2021, p. 27).

### 2.6.3 | Time-frequency domain processing

Time frequency analyses were completed in EEGLAB using the *newtimef* function to apply a complex Morlet wavelet convolution (2 to 9 cycles, 0.5 to 40 Hz, 75 log-spaced frequencies, −3,000 to 3,000 epoch time window, 200 time points per epoch). Data for each frequency were normalized with respect to a pre-stimulus baseline period of −500 to −200 ms using a decibel (dB) transform (dB $= 10 \times \log_{10}$[power/baseline]). Mean activity in the delta (0.5–3.9 Hz) and theta (4–8 Hz) ranges was extracted at FCz during the 250–350 ms after feedback. Studies have found RewP-related delta may be maximal at centro-parietal locations (Cavanagh, 2015), so delta at Cz and Pz were examined as well.

## 2.7 | Analytic strategy

Data were analyzed using IBM SPSS (version 27). For all ANOVAs in which the assumption of sphericity was violated, as indicated by Mauchly's Test of Sphericity, Greenhouse-Geisser corrections were used. To examine our primary ERP dependent variable (i.e., ERP response), we conducted a one-way within-subjects ANOVA on ERP response with feedback (win, loss, draw) as the within-subjects factor. Dependent samples *t*-tests probed significant effects of feedback and Cohen's *d*s ($[M_1 - M_2] / [(SD_1^2 + SD_2^2)/2]$) with 95% confidence intervals were calculated. To test the influence of depression severity and anhedonia severity on ERP response, the BDI-II and the SHAPS were separately added as predictors in ANCOVA models. The effect of depression group on the ERP response was examined in a 2 × 3 mixed ANOVA with feedback (win, loss, draw) as the within-subjects factor and group (depressed, non-depressed) as the between-subjects factor. The above ANOVAs and ANCOVAs were repeated with the other RewP dependent variables: the PCA factors, delta power, and theta power. To reduce Type I error from running multiple ANOVAs, Bonferroni correction was applied to account for the multiple effects across all these ANOVAs/ANCOVAs (see Luck & Gaspelin, 2017).

Memory performance was operationalized by the *unbiased hit rate* (*Hu*), which, because of response bias, uses the differential accuracy score to adjust hit rate (Wagner, 1993). *Hu* has been used previously in source memory studies (e.g., Suzuki & Suga, 2010; Ventura-Bort et al., 2020). Specifically, the *Hu* is derived from multiplying the hit rate for one word type (i.e., the number of correct items of that word type divided by 40) by the differential accuracy score for that word type (i.e., the number of correct items of that word type divided by the number of times the participant classifies a word as that type). Unadjusted hit rate was also reported to provide insight into the extent of task difficulty. A one-way within-subjects ANOVA examined the effect of word type (win, loss, draw, or new) on *Hu*. Significant effects of feedback were followed-up with pairwise comparisons and Cohen's *d*s were calculated. The ANOVA was repeated as ANCOVAs with the BDI-II and the SHAPS as continuous predictors in separate models. The effect of depression group on *Hu* was tested in a 2 × 3 mixed ANOVA with group (depressed, non-depressed) as the between-subjects factor and word type (win, loss, draw, new) as the within-subjects factor. As with the ERP analyses, Bonferroni correction was applied to account for the multiple effects across all memory ANOVAs/ANCOVAs.

The associations between *Hu* for win, loss, and draw words and the corresponding ERP response and the role of depression were examined with three multiple regressions. *Hu*-win (i.e., *Hu* for win words) was regressed on ERP-win (i.e., average ERP response to win feedback in the RewP time window), with BDI-II score and its interaction with ERP-win as additional predictors. This analytic procedure was repeated for the association of *Hu*-loss with ERP-loss and *Hu*-draw with ERP-draw. Due to heteroscedasticity in the regressions, we used

**TABLE 2** Spearman correlations of self-report measures, event-related potentials, and *Hu*

| | BDI-II | SHAPS | ERP-win | ERP-loss | ERP-draw | *Hu*-win | *Hu*-loss | *Hu*-new |
|---|---|---|---|---|---|---|---|---|
| BDI-II | | | | | | | | |
| SHAPS | 0.40*** | | | | | | | |
| ERP-win | 0.09 | 0.04 | | | | | | |
| ERP-loss | 0.13 | −0.02 | 0.81*** | | | | | |
| ERP-draw | 0.11 | 0.05 | 0.82*** | 0.86*** | | | | |
| *Hu*-win | −0.09 | −0.10 | 0.01 | 0.05 | 0.06 | | | |
| *Hu*-loss | 0.07 | 0.00 | 0.18 | 0.23** | 0.14 | 0.31*** | | |
| *Hu*-draw | 0.07 | 0.11 | 0.11 | 0.10 | 0.04 | 0.32*** | 0.35*** | |
| *Hu*-new | 0.07 | 0.14 | 0.18* | 0.17 | 0.17 | 0.21* | 0.24** | 0.16 |

Abbreviations: BDI-II, Beck Depression Inventory-II; ERP, event-related potential in the reward positivity time window; *Hu*, unbiased hit rate; SHAPS, Snaith-Hamilton pleasure scale.

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

the heteroscedasticity standard error estimator in the PROCESS macro for SPSS (Hayes, 2017), which applied bootstrapping with 5,000 samples. Bonferroni correction was applied to account for the multiple effects across these regression analyses. The effect of depression group was tested by comparing the groups' correlations between each ERP variable with its corresponding *Hu* variable. Correlations were compared using bootstrapped confidence intervals and Wilcox's (2009) TWOpov function in R (version 1.4.0).

# 3 | RESULTS

## 3.1 | ERP data quality and reliability

The ERP response RMS(*SME*) values for win (2.19), loss (2.18), and draw (2.10) were less than one-third the size of the standard deviations for win (8.13), loss (7.31), and draw (6.57).[2] This suggests that measurement error contributed less to the variability in ERP response than did true differences between participants (Luck et al., 2021). Split-half reliabilities of the ERPs in each feedback condition were good ($r_{\text{split-half}} = 0.81$ [win], 0.81 [loss], 0.82 [draw]) and Cronbach's alpha across conditions (see Thigpen et al., 2017) was excellent (Cronbach's $\alpha = 0.94$). The low internal consistencies of the RewP difference scores ($r_{\text{split-half}} = 0.27$ [win-loss], 0.21 [win-draw], −0.01 [loss-draw]) and RewP residual scores ($r_{\text{split-half}} = 0.32$ [win regressed on loss], 0.25 [win regressed draw], 0.06 [loss regressed on draw]) were in line with previous research (e.g., Ethridge & Weinberg, 2018) and demonstrated the advantage of using the raw ERP variables in analyses.

## 3.2 | Time domain

ERP responses to win, loss, and draw trials were all strongly correlated (Spearman $r$s = 0.81 to 0.86, $p$s < .001; see Table 2). We first tested the effect of feedback condition alone, which showed a significant main effect of feedback on ERP response, $F(2, 248) = 66.31$, $p < .001$, $\eta_p^2 = 0.35$. Tables 3 and 4 provide the ERP means and statistics for ERP pairwise comparisons. As hypothesized, ERP response to win was significantly more positive than loss and draw ($p$s < .001). ERP response to loss was significantly more positive than draw, $p < .001$ (see Figure 3). We next tested the effects of depression severity (BDI-II), depression group (BDI-II-defined group), and anhedonia severity (SHAPS) on ERP response in separate models. There were no main effects of depression severity, depression group, or anhedonia severity on ERP response ($F$s[1, 123] < 1.09, $p$s > .29) and no interaction of feedback with depression severity, depression group, or anhedonia severity ($F$s[1, 123] < 0.78, $p$s > .50).[3] To explore the null depression and anhedonia

[2]Data quality was found to be similarly acceptable within BDI-II-defined depression groups. High depression group: RMS(*SME*) for win (2.24), loss (2.18), and draw (2.08) were less than one-third the size of the standard deviations for win (9.25), loss (7.24), and draw (6.78); low depressed group: RMS(*SME*) for win (2.19), loss (2.18), and draw (2.14) were less than one-third the size of the standard deviations for win (8.07), loss (7.51), and draw (6.45).

[3]RewP studies have also calculated the RewP as a difference score and as a residual score (e.g., Ethridge & Weinberg, 2018; Levinson et al., 2017). These scores were not reliable in the current study (see Results) but, to compare to previous studies, we examined the ERP response to win minus loss and win minus draw as well as the residual of the ERP response to win regressed on loss and win regressed on draw. Correlations of these measures with the BDI-II and the SHAPS were all non-significant ($r$s = −0.04 to 0.09, $p$s > 0.33). There were also no differences in these RewP measures between depression groups ($p$s > 0.51).

**TABLE 3** Reward positivity means (*SD*) by feedback and depression group in the time domain and time-frequency domain

| | Total ($N = 125$) | | | Low depression ($n = 61$) | | | High depression | | |
|---|---|---|---|---|---|---|---|---|---|
| | Win | Loss | Draw | Win | Loss | Draw | Win | Loss | Draw |
| Time window ERP (μV) | 14.39 (8.13) | 11.55 (7.31) | 10.32 (6.57) | 13.97 (8.07) | 11.56 (7.51) | 10.29 (6.45) | 15.51 (9.25) | 13.07 (7.25) | 11.39 (6.79) |
| PCA factor TF03SF1 (μV) | 12.80 (8.07) | 10.43 (7.03) | 9.23 (6.33) | 12.44 (7.74) | 10.43 (7.26) | 9.14 (6.24) | 14.45 (9.78) | 12.15 (7.12) | 10.46 (6.77) |
| PCA factor TF04SF1 (μV) | 9.25 (5.44) | 6.45 (4.86) | 5.18 (4.66) | 8.49 (5.12) | 6.14 (4.80) | 4.81 (4.53) | 7.88 (5.70) | 5.41 (5.04) | 3.80 (4.74) |
| Time-frequency delta (Hz) | 3.61 (1.93) | 2.86 (1.91) | 2.32 (1.73) | 3.85 (1.81) | 2.96 (1.95) | 2.63 (1.82) | 3.27 (2.14) | 2.87 (2.04) | 2.41 (1.59) |
| Time-frequency theta (Hz) | 2.33 (1.46) | 2.47 (1.58) | 2.34 (1.39) | 2.55 (1.42) | 2.66 (1.71) | 2.49 (1.61) | 2.20 (1.43) | 2.50 (1.64) | 2.25 (1.23) |

*Note:* Time window event-related potential, time-frequency–delta, and time-frequency–theta were measured at FCz from 250 to 350 ms after feedback. Principal component analysis (PCA) factor TF03SF1 was maximal at FCz at 280 ms after feedback. PCA factor TF04SF1 was maximal at FCz at 392 ms after feedback.

Abbreviations: ERP, event-related potential; Hz, hertz; PCA, principal component analysis; RewP, reward positivity; μV, microvolts.

**TABLE 4** Reward positivity dependent samples *t*-test pairwise comparisons in the time domain and time-frequency domain

| | | Win-Loss | | | Win-Draw | | | Loss-Draw | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | *df* | *t* | *p* | *d* [95% CI] | *t* | *p* | *d* [95% CI] | *t* | *p* | *d* [95% CI] |
| *Time window* | | | | | | | | | | |
| ERP (μV) | 124 | 7.13 | <.001 | 0.37 [0.18, 0.55] | 10.56 | <.001 | 0.55 [0.36, 0.74] | 4.19 | <.001 | 0.18 [0.001, 0.354] |
| *PCA factor* | | | | | | | | | | |
| TF03SF1 (μV) | 124 | 6.17 | <.001 | 0.31 [0.13, 0.49] | 10.01 | <.001 | 0.49 [0.31, 0.68] | 4.12 | <.001 | 0.18 [0.001, 0.36] |
| *PCA factor* | | | | | | | | | | |
| TF04SF1 (μV) | 124 | 7.59 | <.001 | 0.54 [0.36, 0.73] | 11.72 | <.001 | 0.80 [0.60, 1.01] | 4.54 | <.001 | 0.27 [0.09, 0.44] |
| *Time-frequency* | | | | | | | | | | |
| Delta (Hz) | 124 | 5.57 | <.001 | 0.39 [0.21, 0.57] | 8.55 | <.001 | 0.70 [0.50, 0.90] | 3.94 | <.001 | 0.30 [0.12, 0.47] |
| *Time-frequency* | | | | | | | | | | |
| Theta (Hz) | 124 | −1.02 | .31 | −0.09 [−0.26, 0.09] | −0.07 | .95 | −0.01 [−0.18, 0.17] | 1.07 | .29 | 0.09 [−0.09, 0.26] |

*Note: Time window ERP*, *time-frequency–delta*, and *time-frequency–theta* were measured at FCz from 250 to 350 ms after feedback. *PCA factor TF03SF1* was maximal at FCz at 280 ms after feedback. *PCA factor TF04SF1* was maximal at FCz at 392 ms after feedback.

Abbreviations: ERP, event-related potential; Hz, hertz; PCA, principal component analysis; RewP, reward positivity; μV, microvolts.

results, we reported in the Supplementary Materials findings on other reward-related variables previously found to be related to the RewP: reward responsiveness (i.e., the behavioral activation system), consummatory anhedonia, anticipatory anhedonia, and love of money.

In order to isolate overlapping ERPs, the analyses were repeated using PCA factors as dependent variables. The temporal PCA with Promax rotation indicated 29 factors for extraction, which accounted for 93.70% of the variance. The spatial PCA with Infomax rotation on each temporal factor indicated that two spatial factors should be extracted, which accounted for 76.48% of the variance. All components with temporal (~200–400 ms) and spatial (i.e., fronto-central) features similar to the RewP were examined as candidates for RewP activity. There were two such factors, both of which were modulated by feedback. The first factor (TF03SF1) accounted for 11.60% of the total variance in the entire epoch and was maximal at FCz at 280 ms and strongly correlated with the mean amplitude ERP for each trial type ($r$s = 0.96). The second factor (TF04SF1) accounted for 3.84% of the total variance of the entire epoch and was maximal at FCz but was less characteristic of the RewP in that it was maximal at 392 ms and only moderately correlated with the mean amplitude ERP for each trial type ($r$s = 0.36 to 0.42; see Supplementary Materials for additional PCA results). Results from the ANOVAs conducted on the two PCA factors aligned with the time-window ERP results. Specifically, there was a

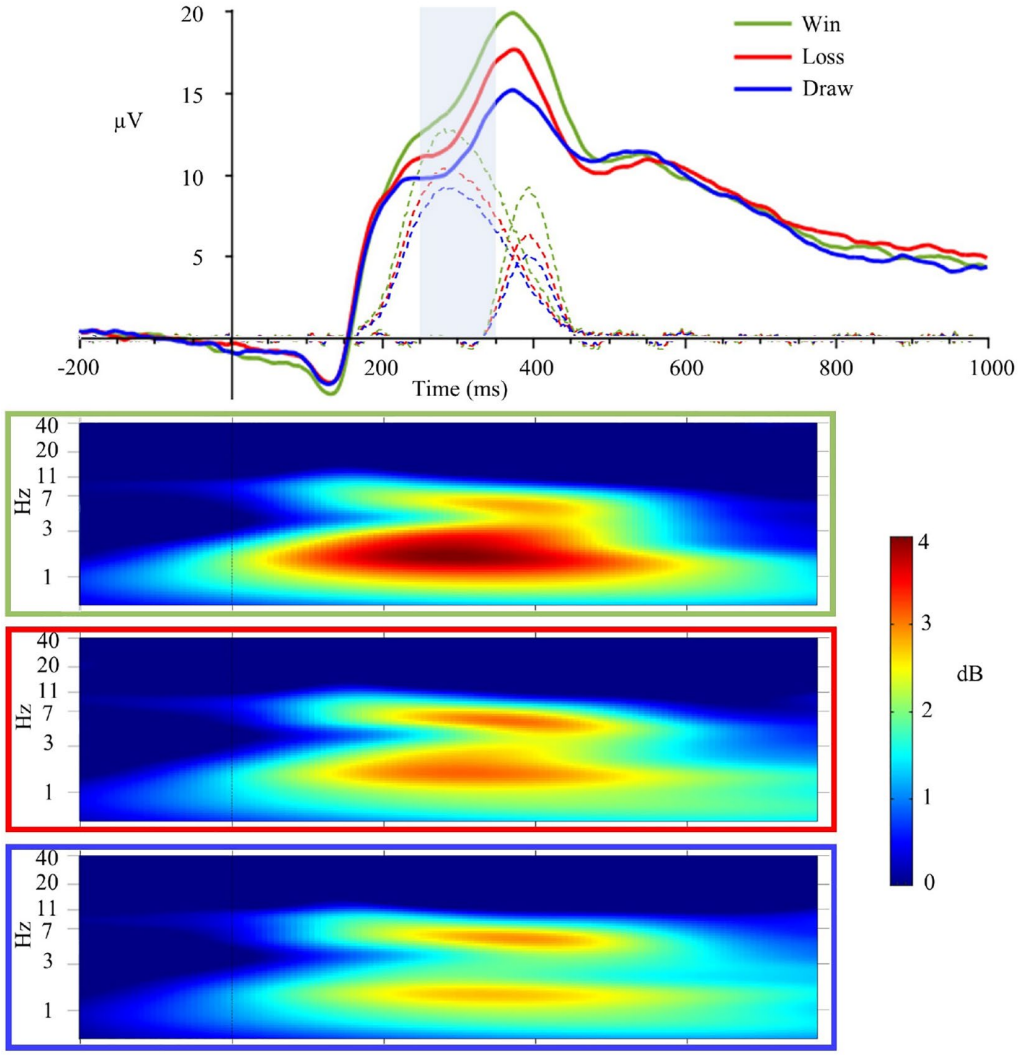


**FIGURE 3** Solid lines represent the time window event-related potential and dashed lines represent the two principal component analysis (PCA) factors. The earlier PCA factor (TF03SF1) peaks at 280 ms and the later PCA factor (TF04SF1) peaks at 392 ms. The heat maps represent the time-frequency data. All data are time-locked to feedback stimulus presentation at the FCz electrode. Shaded bar represents the time window used for measurement. dB, decibels; Hz = hertz; μV = microvolts

significant main effect of feedback on the TF03SF1, $F(2, 248) = 55.13$, $p < .001$, $\eta_p^2 = 0.31$, such that the response to win feedback was significantly more positive than loss and draw feedback, $ps < 0.001$, and the response to loss feedback was significantly more positive than draw feedback, $p < .001$ (see Table 4). A similar effect of feedback was present for the other factor, TF04SF1, $F(248) = 77.77$, $p < .001$, $\eta_p^2 = 0.39$. Response to win feedback was significantly more positive than loss and draw feedback, $ps < .001$, and response to loss feedback was significantly more positive than draw feedback, $p < .001$. For both PCA factors, there were no main effects of depression severity, depression group, or anhedonia severity, $Fs(1, 89) < 1.00$, $ps > .36$, and no interactions with feedback, $Fs(1, 89) < 1.14$, $ps > .28$. All significant time domain results survived Bonferroni correction ($\alpha = 0.0014$).

## 3.3 | Time-frequency domain

The time domain ERP analyses were repeated using delta power and theta power at FCz as the dependent variables.[4] Analyses of delta power revealed the same pattern of results as the time domain ERP. Specifically, there was a main effect of feedback on delta, $F(2, 248) = 42.15$,

[4]Delta power also was examined at Cz and Pz, and the results aligned with those at FCz. There was a main effect of feedback on delta power at Cz, $F(2, 248) = 51.96$, $p < .001$, ηp2 = 0.30, and at Pz, $F(2, 230.18) = 53.32$, $p < .001$, ηp2 = 0.30, with more power for win than loss or draw trials and more power for loss than draw trials, $ps < 0.001$. There were no main effects of the BDI-II, BDI-II-defined depression group, or the SHAPS on delta at Cz or Pz ($ps > 0.24$), nor any interactions with feedback ($ps > 0.27$).

$p < .001$, $\eta_p^2 = 0.25$, such that the response to win was greater than loss and draw and the response to loss was greater than draw ($ps < .001$; see Table 4). There was no main effect of feedback on theta, $F(2, 248) = 0.80$, $p = .45$, $\eta_p^2 = 0.01$ (see Table 4). There were no main effects of depression severity, depression group, or anhedonia severity on either delta or theta ($Fs[1, 89] \leq 0.69$, $ps > .41$) and there were no interactions with feedback ($Fs[2, 246] = < 0.1.07$, $ps > .35$). See Supplementary Material for results on the association of delta and theta with other reward-related variables (i.e., reward responsiveness [behavioral activation system], consummatory anhedonia, anticipatory anhedonia, and love of money). All significant time-frequency domain results survived Bonferroni correction ($\alpha = 0.0014$).

## 3.4 | Memory performance

The unadjusted hit rates for the entire sample were 31% (win), 27% (loss), 29% (draw), and 35% (new), such that win, draw, and new hit rates were significantly higher than chance (25%; $ts(124) = 3.98$ to 5.81, $ps < .001$) and loss hit rate was marginally significantly higher than chance, $t(124) = 1.96$, $p = .05$. The use of *Hu* rather than unadjusted hit rate for analyses was supported by finding response biases in which participants in the high depression group, compared to the low depression group, identified words as "win" fewer times ($M = 33.73$ vs. 41.67, $p = .02$) and "draw" more times ($M = 49.90$ vs. 41.57, $p = .02$). For *Hu*, we first examined the effect of word type alone, which revealed a significant main effect of word type on *Hu*, $F(3, 372) = 20.71$, $p < .001$, $\eta_p^2 = 0.14$. Specifically, *Hu* for win words ($M = 0.105$, $SD = 0.066$) was significantly greater than loss ($M = 0.085$, $SD = 0.062$; $t(124) = 3.80$, $p < .001$, $d = 0.32$) and draw ($M = 0.085$, $SD = 0.049$; $t(124) = 3.58$, $p < .001$, $d = 0.35$) words. *Hu* for loss and draw words were not different ($t(124) = 0.004$, $p = .997$, $d < 0.001$). *Hu* for new words ($M = 0.130$, $SD = 0.087$) was significantly larger than *Hu* for win ($t(124) = -3.28$, $p = .001$, $d = 0.32$), loss ($t(124) = -5.98$, $p < .001$, $d = 0.59$), and draw words ($t(124) = -5.68$, $p < .001$, $d = 0.63$).

Next, we tested the effects of depression severity, depression group, and anhedonia severity on *Hu* in separate models. There were no significant main effects of depression severity or anhedonia severity on *Hu* and no interaction with word type ($Fs[3, 123] < 1.61$, $ps > .20$). There was also no main effect of depression group on *Hu* ($F[1, 89] = 0.61$, $p = .44$), and the interaction between depression group and word type was marginally significant ($F[3, 267] = 2.33$, $p = .08$). Though not significant, this interaction trend was probed in planned dependent samples *t*-tests. The high depression group showed no difference in *Hu* across all word types ($ps > .11$), and of particular interest, *Hu* for win words ($M = 0.089$, $SD = 0.051$) was not different from loss ($M = 0.082$, $SD = 0.048$; $t(29) = 0.65$, $p = .52$, $d = 0.13$) or draw ($M = 0.094$, $SD = 0.056$; $t(29) = -0.36$, $p = .72$, $d = -0.09$). However, the low depression group showed significantly greater *Hu* for win words ($M = 0.111$, $SD = 0.074$) compared to loss ($M = 0.088$, $SD = 0.075$; $t(60) = 2.94$, $p < .01$, $d = 0.31$) and draw ($M = 0.080$, $SD = 0.047$; $t(60) = 4.61$, $p < .001$, $d = 0.51$) and significantly greater *Hu* for new words ($M = 0.131$, $SD = 0.09$) compared to loss ($t(60) = 4.65$, $p < .001$, $d = 0.50$) and draw ($t(60) = 4.89$, $p < .001$, $d = 0.68$; see Figure 4). Comparisons of *Hu* variables between depression groups showed no significant differences (*Hu*-win: $t(89) = 1.50$, $p = .14$; *Hu*-loss: $t(89) = 0.40$, $p = .69$; *Hu*-draw: $t(89) = 1.23$, $p = .22$; *Hu*-new: $t(89) = 1.16$, $p = .25$). All significant memory performance results survived Bonferroni correction ($\alpha = 0.0071$).

## 3.5 | Memory and RewP response

The correlations between RewP and *Hu* variables are shown in Table 2 and results of multiple regression analyses with standardized betas are reported here. Neither ERP-win ($\beta = 0.07$, $p = .47$) nor its interaction with depression severity ($\beta = -0.11$, $p = .19$) predicted *Hu*-win, $F(3, 121) = 0.73$, $p = .54$, $R^2 = 0.01$. ERP-loss predicted *Hu*-loss ($\beta = 0.21$, $p = .04$), but this was not significant following Bonferroni correction ($\alpha = 0.008$) and the full model predicting *Hu*-loss was not significant, $F(3, 121) = 2.48$, $p = .07$, $R^2 = 0.07$. The interaction between ERP-loss and depression severity did not predict *Hu*-loss ($\beta = -0.15$, $p = .11$). ERP-draw did not predict *Hu*-draw ($\beta = -0.04$, $p = .67$), but its interaction with depression severity did ($\beta = -0.22$, $p = .03$) and the Johnson-Neyman test showed that ERP-draw was negatively associated with *Hu*-draw for people with a BDI-II score ≥21 (i.e., moderate and severe depression; $n = 23$). However, this interaction was not significant following Bonferroni correction ($\alpha = 0.008$) and the full model predicting *Hu*-draw was not significant, $F(3, 121) = 1.70$, $p = .17$, $R^2 = 0.05$. An exploratory path analysis was conducted to isolate the unique associations between each ERP variable and the corresponding *Hu* variable; results aligned with the trends reported here (see Supplementary Materials). Finally, there were no significant depression group differences in the correlations between ERP and *Hu* variables (win: $r_{\text{lowdep}} = 0.12$ [−0.15, 0.32], $r_{\text{highdep}} = -0.05$ [−0.29, 0.28], $r_{\text{difference}} = 0.18$ [−0.26, 0.54]; loss:

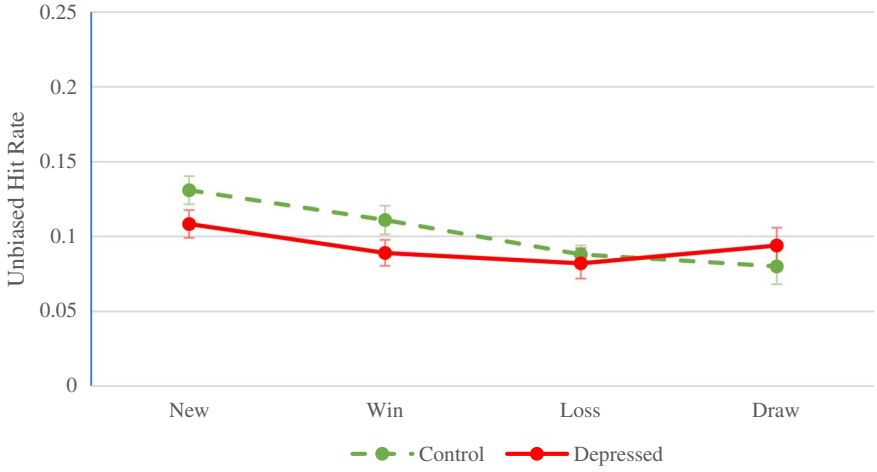


**FIGURE 4** Unbiased hit rate is the hit rate for one word type (i.e., number of hits divided by 40) multiplied by the differential accuracy score for that word type (i.e., number of hits divided by the number of times the participant classified a word as that type). Error bars represent standard error of the mean

$r_{\text{lowdep}} = 0.32$ [0.09, 0.53], $r_{\text{highdep}} = -0.02$ [−0.41, 0.45], $r_{\text{difference}} = 0.34$ [−0.12, 0.73]; draw: $r_{\text{lowdep}} = 0.17$ [−0.14, 0.43], $r_{\text{highdep}} = -0.24$ [−0.57, 0.35], $r_{\text{difference}} = 0.41$ [−0.09, 0.80]).

## 4 | DISCUSSION

This study aimed to evaluate the potential of the RewP as a biomarker of reward responsiveness and depression by addressing limitations of the doors task and examining the RewP's association with both continuous and categorical depression as well as anhedonia. As predicted, the ERP response to win feedback was more positive than the response to loss and draw (i.e., neutral) feedback. Contrary to prior research, the ERP response to loss was significantly more positive than the response to draw. Confidence in these results is bolstered by finding identical results when examining underlying factors of the ERP, as defined by PCA, which appeared to isolate the RewP candidate factor from anterior P3a and posterior P3b factors (see Figure 3 and Supplementary Materials). Further, delta frequency showed the same pattern of differences between win, loss, and draw feedback, while theta frequency was not differently affected by any feedback type. Sample size may have limited previous RewP studies that used doors-like tasks with draw trials (*N*s = 10 to 23; Hajcak et al., 2006; Holroyd et al., 2004; Holroyd et al., 2006). Indeed, two such studies showed qualitative, but non-significant, differences between loss and draw trials (Hajcak et al., 2006; Holroyd et al., 2006), and Holroyd and colleagues (2006) reported an effect size ($d = 0.16$) that was similar to the current study ($d = 0.18$). Previous research may have been underpowered to detect this small effect. Finding that ERP response to loss was more positive than response to draw stands in contrast to a dominant assumption that loss and draw responses are the "baseline response" (Proudfit, 2015, p. 450) and indicates that a more positive ERP in the RewP time window does not simply represent greater reward valuation.

The current findings address whether the RewP is modulated by salience or valence. The findings of greater amplitude for win versus loss feedback and loss versus draw feedback suggest that the RewP responds to feedback salience in addition to valence. These findings were supported by the apparent effects of salience in the PCA and time-frequency analyses, which failed to identify an underlying component of the RewP that only responded to reward. Activation was more positive for reward than loss trials, yet it is unclear whether or not this might be due to differences in the magnitude of win (+$0.50) and loss (−$0.25) feedback. Indeed, previous research suggests that feedback magnitude differences can modulate ERP activity in the RewP time window (Rawls & Lamm, 2021; Sambrook & Goslin, 2015, 2016). Our results are consistent with other research that shows the RewP is modulated by salience (Nieuwenhuis et al., 2004; Rawls et al., 2020; Soder & Potts, 2018; Talmi et al., 2013). Results also align with a recent RewP study that used social feedback to show that the ERP response to positive feedback was larger than negative feedback, which was larger than neutral feedback (Funkhouser et al., 2020). Our finding that win and loss feedback both differed from draw feedback suggests that activity in the RewP time window may reflect a salience prediction error (SPE) to some degree. As such, activity in the RewP time window may represent the feedback's motivational relevance, not only its reward or loss valence. The larger ERP response to reward feedback is consistent with the RewP being sensitive to valence and reflecting a reward prediction error (RPE), in which dopamine signals trigger an increase in ERP amplitude following rewarding but not loss stimuli (Heydari & Holroyd, 2016; Holroyd & Coles, 2002). Our results are consistent with the RewP comprising both an SPE and RPE, as these interpretations are not mutually exclusive

(Sambrook & Goslin, 2015). Past studies have found separable reward and loss activity underlying the RewP (Foti et al., 2015; Rawls & Lamm, 2021; Rawls et al., 2020; Sambrook & Goslin, 2016), but this was not the case in our PCA or time-frequency data. Overall, our results showcase that both salience and valence significantly impact the RewP. The findings point to a need for additional research to examine the roles of salience and valence in ERP responses to reward and loss.

The current study further sought to clarify the RewP-depression association by analyzing both continuous and dichotomous depression in a relatively large undergraduate sample. Although MDD diagnosis was not assessed, we used an a priori strategy to dichotomize depression severity into groups to approximate the group analysis approach that is common in the RewP literature. Results did not show that the RewP was significantly associated with continuous depression severity or that it differed between high depression and low depression groups. These results align with other studies that did not find a simple relation between the RewP and self-reported depression (Ait Oumeziane et al., 2019; Distefano et al., 2018; Foti et al., 2011) or anhedonia (Foti et al., 2014; Padrão et al., 2013; Umemoto et al., 2019). Interestingly, some studies have found that a larger RewP is associated with *greater* depression (Berry et al., 2019; Mueller et al., 2015; Webb et al., 2017) or anhedonia (Chen et al., 2018). Further, the RewP may be only associated with persistent depression, not current depression (Bowyer et al., 2019), or only associated with depression when combined with impulsivity (Ait Oumeziane & Foti, 2016; Novak et al., 2016). We add to these studies by showing null effects of continuous depression severity, BDI-II-defined depression group, and anhedonia severity across a range of RewP outcome measures (i.e., time window ERP, PCA factors, and delta and theta power).

However, given that meta-analyses have reported significant small or small-to-medium effects of depression on the RewP (Clayson et al., 2020; Keren et al., 2018), we caution against generalizing the current results to mean there is no relation between the RewP and depression. Instead, this study highlights the importance of methodology in RewP studies on depression. For example, the RewP's association with depression may be more robust in those with a clinical diagnosis of MDD (Clayson et al., 2020) and may be smaller when using certain task designs (Chang et al., 2020; Moran et al., 2017). Despite attempts to reduce extraneous cognitive or emotional processes—by training participants to easily identify the meaning of the feedback colors and using common and emotionally neutral words—the stimuli were more complex than in typical doors tasks. Increased feedback complexity has been shown to decrease the RewP amplitude (Cockburn & Holroyd, 2018; Krigolson et al., 2012, 2015) and may have systematically reduced the effect of depression. For instance, poor cognitive control associated with depression (see Paulus, 2015) may have increased cognitive interference from the word stimuli when processing feedback value. Further, the RewP is impacted by reward frequency (Frömer et al., 2016) and the type of available feedback options (e.g., Watts & Bernat, 2018; Zheng et al., 2017). As such, increasing the proportion of non-reward options through the addition of draw trials may have increased the psychological value of reward trials and diluted the effect of depression. The current study also modified the doors task by counterbalancing which colors and words were associated with win, loss, and draw. Counterbalanced stimuli reduced the risk that the current findings were confounded by the physical properties of the stimuli and controlled for the possibility that individuals with depression have a unique RewP response to particular colors. Even after these modifications, when compared to studies that used the original doors task in similar samples (Berry et al., 2019; Bowyer et al., 2019; Distefano et al., 2018; Tunison et al., 2019), the win-loss effect size in the current study ($d = 0.37$) was similar to and within the range of effect sizes of those previous studies ($ds$ =0.32, 0.41, 0.64, and 0.50, respectively). When designing future RewP tasks, researchers should consider the costs and benefits of using complex stimuli, neutral trials, and counterbalanced stimuli and identify the parameters under which the RewP may serve as a consistent biomarker of depression.

Memory performance results showed that the high depression group remembered the value (win, loss, or draw) presented with each type of word equally. In contrast, the low depression group remembered the value of words presented on win trials at a significantly higher rate than words presented on loss or draw trials. As such, compared to participants in the low depression group, the high depression group showed a deficit in memory for the rewarding context in which words were encoded (i.e., source memory). The current data agree with a previous finding that depressed individuals lacked the typical source memory bias toward reward over neutral stimuli (Dillon et al., 2014). We extend previous work by showing that individuals with elevated depression also lacked the typical source memory bias toward reward over *loss* stimuli and were not biased toward better memory of loss stimuli. These findings highlight the importance of the lack of positive memory bias in source memory, rather than a negative memory bias. Further, memory response biases were observed such that individuals high in depression, compared to those low in depression, were less likely to recall that a stimulus was rewarding ("win") and more likely to recall that it was neutral ("draw"). Our results

encourage the development and implementation of memory bias modification techniques that focus on positive memories (e.g., Arditte Hall et al., 2018; Dalgleish & Werner-Seidler, 2014; Visser et al., 2020). Though the high depression and low depression groups showed different memory patterns in the pairwise comparisons, the marginal significance of the group by word type interaction suggests additional research should explore the robustness of the source memory findings.

Source memory was found to have small associations with the RewP, but they were not significant following Bonferroni correction. Specifically, a greater ERP response to loss was marginally related to increased source memory for loss words. There was also a trend for a *smaller* ERP response to draw to be related to increased source memory for draw words only at higher levels of depression severity. Notably, we found no evidence that the RewP was associated with memory for win stimuli, in contrast to a previous study that found that the RewP was related to increased recognition memory for pictures that indicated positive feedback (Höltje & Mecklinger, 2018). Researchers have proposed that positive errors in the prediction of reward (i.e., RPEs) facilitate reward-related memory formation by triggering the release of dopamine, a process that may be impaired by depression (Dillon, 2015; Dillon & Pizzagalli, 2018). However, the current study did not observe a link between a putative RPE (i.e., the RewP) and reward-related source memory. In light of the previously described uncertainty about whether the RewP is an RPE and whether the RPE component can be isolated, it is possible that the RewP may not represent the dopaminergic neural firing that is hypothesized to link reward response to memory formation. The marginal significance of the current findings with loss and draw stimuli and the limited prior research suggest that more studies are needed before drawing conclusions about connections between the RewP and memory.

Several limitations should be considered when interpreting this study's findings. It is possible that the P3, which overlaps the RewP in time (300–600 ms) and responds to salience, contributed to the ERP in the RewP time window (Glazer et al., 2018). However, we increased our ability to isolate the RewP by separating out possible P3a and P3b factors with PCA, choosing an a priori RewP time window, and using counterbalanced and equiprobable stimulus conditions to avoid oddball and physical feature effects known to influence the P3 (e.g., Gaeta et al., 2003; Verleger, 2020). This study fell short of the 128 participants (64 in each group) needed for 0.80 power to detect a medium depression-RewP effect (see Clayson et al., 2020), though we did obtain a larger sample size than typical RewP studies (see Clayson et al., 2020), including those with null findings (Ait Oumeziane et al., 2019; Distefano et al., 2018; Foti, Weinberg, et al., 2011). Although studies with larger samples are needed, it is notable that the correlations between depression and the RewP variables were very small ($r$s = 0.00 to 0.13). Generalizability of the results are restricted by the use of an undergraduate convenience sample that was three-quarters women. The relation between ERP responses to win, loss, and draw trials may be different in non-undergraduate samples, such as in a recent adolescent sample (Hammond et al., 2021). Participants' depression was determined using self-reported depression severity, but self-reported depression in undergraduate students may be intertwined with developmental factors (e.g., academic or peer-related stressors) and be less reflective of MDD. Other types of rewards (e.g., social rewards) may be more relevant to college student's depression than monetary reward (Distefano et al., 2018). Although unadjusted hit rates for the full sample were significantly higher than chance, they remained numerically close to chance and possibly indicate a floor effect. Employing a less challenging memory task that allows for a higher hit rate may improve the ability to detect the associations between source memory, depression, and the RewP. Although the current study aimed to improve the doors task, several unaddressed factors may also affect the RewP (e.g., reward magnitude and subjective reward expectancy; Glazer et al., 2018).

In summary, the current study highlights the impact of salience on the RewP and agrees with other research that suggests the RewP may not be purely a response to reward. In a relatively large sample of undergraduates, this study failed to find an association between the RewP and depression or anhedonia. The high depression group showed a deficit in reward-related source memory, but the small relations between memory performance and the RewP were not robust. Results suggest that researchers should recruit samples that are large enough to detect small ERP effects and incorporate a neutral condition into study tasks to assess for the effects loss on the RewP. Given that the RewP has been shown to assist in the prediction (Hausman et al., 2018; Nelson et al., 2016), diagnosis (Bowyer et al., 2019), and treatment (Barch et al., 2020; Burkhouse et al., 2016, 2018) of depression, further research to advance the interpretation of the RewP has the potential to profoundly impact depression research and clinical practice.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## AUTHOR CONTRIBUTIONS

**Nathan Hager:** Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation;

Methodology; Visualization; Writing-original draft. **Matt Judah:** Conceptualization; Data curation; Formal analysis; Funding acquisition; Methodology; Resources; Supervision; Visualization; Writing-review & editing. **Eric Rawls:** Validation; Writing-review & editing.

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## SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of the article at the publisher's website.

**FIGURE S1** Principal component analysis (PCA) factor maximal at Pz and 483 ms

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