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Effects of Reward Context on Feedback Processing as Indexed by Time-Frequency Analysis

Adreanna T. M. Watts and

Department of Psychology, University of Maryland, College Park

Edward M. Bernat

Department of Psychology, University of Maryland, College Park

Abstract

The role of reward context has been investigated as an important factor in feedback processing. Previous work has demonstrated that the amplitude of the feedback negativity (FN) depends on the value of the outcome relative to the range of possible outcomes in a given context, not the objective value of the outcome. However, some research has shown that the FN does not scale with loss magnitude in loss-only contexts, suggesting that some contexts do not show a pattern of context-dependence. Methodologically, time-frequency decomposition techniques have proven useful for isolating time-domain ERP activity as separable processes indexed in delta (< 3 Hz) and theta (3–7 Hz). Thus, the current study assessed the role of context in a modified gambling feedback task using time-frequency analysis to better isolate the underlying processes. Results revealed that theta was more context-dependent and reflected a binary evaluation of bad vs. good outcomes in the gain and even contexts. Delta was more context-independent: good outcomes scaled linearly with reward magnitude and good-bad differences scaled with context valence. Our findings reveal that theta and delta are differentially sensitive to context and that context valence may play a critical role in determining how the brain processes feedback.

1. Introduction

Reward processing and performance monitoring have been widely studied as important factors underlying cognitive and affective processes. Reward and performance monitoring systems are necessary for the adaptation of behavior in the pursuit of goals. Furthermore, these systems have been implicated in various forms of psychopathology, such as depression, anxiety, substance abuse, and behavioral addictions (Moser, Moran, Schroder, Donnellan, & Yeung, 2013; Nutt, Lingford-Hughes, Erritzoe, & Stokes, 2015; Pizzagalli, 2014; Treadway & Zald, 2013). One important aspect of reward processing is the context in which positive and negative feedback occurs, or the reward context (Holroyd, Larsen, & Cohen, 2004; Kujawa, Smith, Luhmann, & Hajcak, 2013; Nieuwenhuis et al., 2005). Previous work has demonstrated that the amplitude of the feedback negativity (FN), a negative-going event-related potential (ERP) peaking around 250 ms, depends on the value of the outcome relative to the range of possible outcomes in a given context, not the

objective value of the outcome (Holroyd et al., 2004). However, some research has shown that the FN does not scale with loss magnitude in loss-only contexts, suggesting that some contexts do not show a pattern of context-dependence reflected in FN amplitude (Holroyd et al., 2004; Kujawa et al., 2013).

Methodologically, time-frequency decomposition techniques have proven useful for isolating important activity in the FN and other components, and have shown that time-domain ERPs can be better represented as separable processes in delta (< 3 Hz) and theta (3–7 Hz) (Baar, Baar-Eroglu, Karaka, & Schürmann, 2001; Bernat, Malone, Williams, Patrick, & Iacono, 2007; Cavanagh, Zambrano-Vazquez, & Allen, 2012; M. X. Cohen, Elger, & Ranganath, 2007; Demiralp, Ademoglu, I Stefanopulos, Baar-Eroglu, & Baar, 2001). Furthermore, recent work has suggested that differences in FN amplitude are due in large part to the superposition of a reward positivity (RewP) component, primarily composed of delta activity, and a negative-going deflection consisting of theta activity (Bernat, Nelson, Holroyd, Gehring, & Patrick, 2008; Holroyd, Pakzad-Vaezi, & Krigolson, 2008). These frequencies have been shown to index different aspects of feedback processing. Work from our group has suggested that theta is most sensitive to more primary stimulus characteristics, like gain vs. loss feedback, while delta has been shown to index both primary and more complex secondary features, like outcome magnitude, relative outcome, and expectancy (Bernat, Nelson, & Baskin-Sommers, 2015; Watts, Bachman, & Bernat, 2017). Thus, while there has been important attention on time-frequency decomposition of the FN (Bernat et al., 2015, 2008; Bernat, Nelson, Steele, Gehring, & Patrick, 2011; Foti, Weinberg, Bernat, & Proudfit, 2015; Proudfit, 2015; Watts et al., 2017), the current study will provide information about whether the role of context in feedback processing is better elucidated using time-frequency analysis. Specifically, we will assess whether theta indexes more basic, context-dependent processing across contexts and whether delta reflects more complex, context-independent processing across contexts.

1.1 Context and Feedback Processing

The initial investigations of the role of context in feedback processing utilized ERP (Holroyd et al. 2004) and fMRI (Nieuwenhuis et al., 2005) methodologies. Reward context was operationalized by employing a modified gambling task, in which gain, even, and loss contexts were presented in blocks of trials. These studies evaluated the context-dependence versus independence of the FN (Holroyd et al., 2004) and BOLD response (Nieuwenhuis et al., 2005). Context-dependence refers to the processing of outcomes in a relative manner within each context, whereas context-independence refers to the processing of outcome values in an absolute manner, independent of context. Two criteria were required for context-dependence: 1) identical outcome values were evaluated differently across contexts (e.g., the zero outcomes in the gain and loss contexts) and 2) the same outcome levels (e.g., best outcomes) were processed similarly across contexts where outcome levels scaled with reward magnitude within context (Holroyd et al., 2004). Alternatively, the following criteria were required for context-independence: 1) identical outcome values were evaluated similarly across contexts and 2) the same outcome levels were processed differently across contexts (Holroyd et al., 2004). Results revealed that the FN and BOLD response met criteria for context dependence in some but not all cases (Holroyd et al., 2004; Nieuwenhuis

et al., 2005). Importantly, the breaking even outcome accounted for outcome differences in the loss context, as differences were not seen between varying loss magnitudes. Because a breaking even outcome was included in each context, the contexts did not purely reflect one type of outcome valence (either all gains or all losses). If the breaking even outcomes were removed and only valenced outcomes were considered, FN and BOLD differences would only be seen in gain-possible contexts (i.e., gain and even) but not in the loss context (see Table 1). Thus, the loss context does not show a pattern of context-dependence when only the loss-valenced outcomes are considered. Taken together, these findings suggest that the FN and BOLD response may reflect a combination of context-dependent and independent processing, influenced by both the type of context and the breaking even outcome.

The initial investigations on reward context separated contexts into blocks of trials within the task (Holroyd et al., 2004; Nieuwenhuis et al., 2005), but more recent work has investigated how feedback processing is influenced by micro vs. macro-level contexts. Kujawa et al. (2013) evaluated the context-dependence of the FN by manipulating outcomes on a trial level with different cues for gain and loss outcomes (local outcomes) versus a task level (global outcomes). Results revealed that breaking even for gain (+0) and loss (−0) cues and losing (−25) were associated with similar FNs (see Table 1; Kujawa et al., 2013). FN was found to be a binary representation of favorable (+50) compared to unfavorable outcomes (+0, −0, −25), which suggests that the FN is more sensitive to global than local contexts (Kujawa et al., 2013). These results indicate that outcomes are not processed in a relative, context-dependent manner when the context changes at a local, trial level. Rather, context-dependent processing may be differentially elicited when trials are presented in a sustained block representing one context, as shown by the global context in Kujawa et al. (2013) and the block designs in Holroyd et al. (2004) and Nieuwenhuis et al. (2005). These results are consistent with ERP work from our group on emotion regulation, which has shown that affective modulation in response to instruction cues does not occur on a trial-by-trial basis but does occur in a sustained block of trials with the same instructional cue (Bernat, Cadwallader, Seo, Vizuetta, & Patrick, 2011).

1.2 Time-domain vs. Time-frequency Analysis

Conventional FN measures have traditionally been associated with negative feedback because the component is diminished or absent following positive feedback (Gehring & Willoughby, 2002; Miltner, Braun, & Coles, 1997); however, more recent work has suggested modulation of the FN by positive feedback. Bernat et al. (2008) and Holroyd et al. (2008) provided initial evidence of a reward positivity (RewP) component, which is enhanced for positive relative to negative feedback. This research and other recent work has indicated that smaller negative FN amplitude elicited by positive feedback is partially explained by the superposition of a heightened slow, positive waveform, the RewP (Bernat et al., 2008; Foti, Weinberg, Dien, & Hajcak, 2011; Holroyd et al., 2008; Kujawa et al., 2013; Proudfit, 2015). Time-frequency analysis suggests that the RewP is composed primarily of delta activity, not theta (Bernat et al., 2011; Bernat et al., 2015). Recent work based on temporal-spatial principal component analysis (PCA; Carlson, Foti, Mujica-Parodi, Harmon-Jones, & Hajcak, 2011; Foti et al., 2011; Weinberg, Riesel, & Proudfit, 2014) and time-frequency PCA (Bernat et al., 2015, 2008; Bernat, Nelson, et al., 2011; Foti et al., 2015) has

indexed a positive-going deflection of delta band activity that is in the time range of the FN and increased for gains relative to losses. Additionally, this RewP component has been shown to be sensitive to reward magnitude (Bernat et al., 2015, 2008; Holroyd, Krigolson, & Lee, 2011; Holroyd et al., 2008), relative outcome (Bernat et al., 2015), and outcome expectancy (Cavanagh, 2015; Holroyd et al., 2011, 2008; Watts, Bachman, & Bernat, 2017), but the influence of context on the RewP has not yet been evaluated.

Delta activity associated with the RewP is partially responsible for modulations in FN, but time-frequency analysis has revealed that the FN is composed of theta activity as well (Gehring & Willoughby, 2004). Regression analyses using time-frequency components as predictors and the FN as the outcome measure have revealed that delta and theta contribute unique sources of variance to the FN, such that increased theta reflects losses and increased delta is associated with gains (Bernat et al., 2015, 2008; Bernat, Nelson, et al., 2011; M. X. Cohen et al., 2007; Nelson, Patrick, Collins, Lang, & Bernat, 2011; Watts et al., 2017). These findings provide strong evidence that separable neural activity indexing losses and gains contribute to the FN. Foti and colleagues (2015) extended this work by applying source localization to time-frequency measures of the FN, where two distinct neural generators were identified. Loss-related theta activity was localized in the ACC, while gain-related delta activity was focused in the striatum (Foti et al., 2015). These results indicate that theta and delta index separable processes underlying the time-domain FN; thus, processes associated with outcome valence can be clarified by time-frequency analytic approaches.

Previous research has also shown that when outcome stimuli in a gambling task provide multiple pieces of information, theta is sensitive to the most primary or salient stimulus attributes (often outcome valence – loss vs. gain), while delta is modulated by primary as well as more complex secondary characteristics, such as reward magnitude and expectancy (Bernat et al., 2015; Watts et al., 2017). This work provides further support that time-frequency theta and delta measures are useful for isolating multiple feedback processes.

1.3 Considerations based on previous work

The current study seeks to build on previous work investigating the role of context in reward processing by utilizing time-frequency analysis of the FN. Previous research using ERP and fMRI methodology has provided important considerations for understanding the context-dependence of reward processing. Namely, the breaking even outcome has led to results showing context-dependent processing in all contexts. However, when only valenced outcomes are considered (i.e., gains and losses), context-dependent processing is only seen in gain-possible contexts, as no differences exist between varying loss magnitudes in the loss context. Furthermore, context-dependent processing seems to be limited to tasks in which trials for a given context are presented in a sustained block. Lastly, the ERP studies investigating context used time-domain analysis of the FN, which is problematic due to research showing that the FN contains separable underlying processes indexed in delta and theta frequency bands.

1.4 Current Study

The current study utilized a modified version of the gambling task created by Holroyd et al. (2004), with one key difference: the task did not include a breaking even outcome in each context. In removing the breaking even outcome, the current study aims to assess processing variations across contexts that purely reflect one type of outcome (all gains or all losses) or a combination of both types (as in our even context). Because only two outcomes were possible in each context, the better outcome will be referred to as “good” and the worse outcome will be referred to as “bad.”

This study assessed three primary aims. The first aim was to evaluate whether theta is primarily context dependent. Previous research has suggested that theta represents a binary evaluation of feedback as good or bad (Bernat et al., 2015; Watts et al., 2017), and thus we predict the following (as illustrated in Figure 1):

- 1a.** Theta will be associated with similar good-bad differences across contexts (context-dependence).
- 1b.** Theta activity will be different between outcomes of the same absolute value across contexts, such as +5 in the gain context and +5 in the even context (context-dependence).

The second aim was to investigate whether delta reflects a combination of context-dependent and context-independent processing. Previous work has shown that delta is increased for reward outcomes and is sensitive to a number of different processes operating across lower frequencies, including outcome magnitude, expectancy, and relative outcome (Bernat et al., 2015; Watts et al., 2017). We thus hypothesize as follows (see Figure 1):

- 2a.** Delta in response to good outcomes across contexts will be associated with increases in amplitude linearly related to the amount of reward (context-independence).
- 2b.** Good-bad differences in delta will be attenuated in the loss condition, relative to the even and gain conditions given previous literature showing ERP differences only in gain-possible contexts (context-independence).
- 2c.** Delta activity will be different between outcomes of the same absolute value across contexts, such as +5 in the gain context and +5 in the even context (context-dependence).

A third aim in this study is to assess conventional time-domain FN amplitude and context-related processing. Based on previous literature, we expect FN to show a combination of context-dependence and independence. Given that the time-domain FN contains multiple frequency bands reflecting separable processes, we do not propose specific hypotheses regarding the relationship between context and the FN. However, we do expect theta and delta to contribute unique sources of variance to the FN as previous research has shown (Bernat et al., 2015, 2008; Bernat, Nelson, et al., 2011; Foti et al., 2015; Nelson et al., 2011; Watts et al., 2017).

2. Method

2.1 Participants

Participants ($n = 152$) were recruited from undergraduate students at Florida State University. Five participants were excluded due to a problem with the EEG recording (e.g., experimenter error or software malfunction) and fifteen participants were excluded due to an excessive number of EEG artifacts ($>33\%$ of trials rejected using methods described below). The final sample contained 132 participants 18 years of age or older (80 females; M age = 19.99, $SD = 3.52$). The final sample was not significantly different than the original sample on key demographic variables, including gender and age. Participants were screened for visual impairments, neurological conditions, and/or traumatic brain injuries. Participants were provided informed consent before starting the study and were offered monetary compensation (\$10/hr) or course credit for participation.

2.2 Procedures

EEG data were collected in a sound-attenuated, dimly lit room. Experimental stimuli were presented on a 21-inch Dell high-definition CRT color monitor, centrally placed at a viewing distance of 100 cm, subtending a visual angle of 3.5° . E-Prime version 1.1 was used to present the stimuli, and a PST Serial Response Box (Psychology Software Tools, Inc.) was used to collect responses to the task.

Participants performed a modified version the gambling task used in (Holroyd et al., 2004), as shown in Figure 2. Each trial consisted of two circles presented side-by-side with a black border and white background. Participants were instructed to select one of the circles by pressing the left or right button on the button box. The circles remained on the screen until the participant made a selection, at which time the selected circle turned red. 1000 ms after the selected circle turned red, the participant received monetary feedback inside the circle, which was displayed for 1000 ms. Good and bad outcomes were possible in each of three contexts: +5 or +15 in the gain context, +5 or -5 in the even context, and -5 or -15 in the loss context. The task was divided into six blocks, with two blocks for each context (i.e., gain, even, and loss). Each block consisted of 24 trials, resulting in 48 trials per context and a total of 144 trials. Blocks were counterbalanced across participants such that no one context was presented in two consecutive blocks. Participants were informed of the context type before each block. They were also told they should respond in a way that maximized their earnings, and that they would be given a monetary reward associated with their performance at the end of the task. Unbeknownst to the participants, the two outcomes in each block were presented at random with an equal probability. All participants were given \$5.00 at the end of the task. Before the task began, participants completed a brief practice.

2.3 Psychophysiological Data Acquisition

Data were recorded using a Neuroscan 128-channel Quik-Cap (sintered Ag-Ag/Cl; non-standard layout) as well as a 128-channel Synamps RT amplifier (Neuroscan, Inc.). Horizontal electrooculogram activity was recorded from electrodes placed on the outer canthus of both eyes, while vertical electrooculogram activity was recorded from electrodes placed above and below the left eye. Ten electrodes around the ears were removed from

analysis due to inconsistent connection to the scalp across participants, leaving a total of 113 EEG channels. Impedances were kept below 10 k Ω . EEG signals were vertex referenced during recording (directly between Cz and CPz), and re-referenced to averaged mastoid signals offline, collected using an analog 0.05 to 200 Hz bandpass filter and digitized at 1000 Hz using Neuroscan Acquire (Neuroscan, Inc.).

2.4 Data Preprocessing

Epochs of three seconds were then taken from 1000 ms pre- to 2000 ms post-outcome stimulus onset with a 150 ms pre-stimulus baseline, and were re-referenced to averaged mastoid sites. Ocular artifacts were corrected with a regression-based algorithm developed by Semlitsch, Anderer, Schuster, & Presslich (1986) in the Neuroscan Edit 4.5 software (Neuroscan, Inc.) and downsampled to 128 Hz using the Matlab resample function (Mathworks, Inc.), which utilizes an anti-aliasing filter before resampling. Then, two criteria for data cleaning were used. In the first, trials were rejected if activity at F3 or F4 exceeded ± 100 μ V in either the pre-stimulus period of -1000 to -1 ms or the post stimulus period of 1 to 2000 ms, to remove larger face or eye artifacts not appropriately handled by the Semlitsch algorithm. For the second criterion, trials were rejected if activity in any electrode exceeded ± 150 μ V during the same pre- and post-stimulus time periods. Together, these removed 9.1% of all trials from analysis. Visual analysis of the averaged waveforms indicated that 0.002% of electrodes were disconnected during recording and were replaced with the mean of the nearest neighbors. After preprocessing, data were averaged according to the six different outcomes specified above under 2.2 Procedures.

2.5 Data Averaging

Although data cleaning improves the quality of the data, it removes trials, leaving an uneven number of trials across outcome types and participants. Resampling and bootstrapping methods are well-defined and widely implemented techniques for estimating population parameters (Efron, 1982). While an important benefit of resampling techniques in general are the improved estimates of population parameters, the primary purpose of implementing these techniques was to remove any bias associated with uneven trials counts by equating the number of trials in each subject-electrode-condition average. Indeed, previous research has shown that the number of trials used in each average affects the reliability of the measures extracted from ERPs (J. Cohen & Polich, 1997; Olvet & Hajcak, 2009; Pontifex et al., 2010; Steele et al., 2016). Thus, in the current study, resampling and bootstrapping methods used in previous research (Watts et al., 2017) were employed. Subsets of five trials for each outcome were subsampled 50 times with replacement. Next, these sets of 50 resampled averages for each outcome type were bootstrapped 500 times. Integrity of each waveform was preserved during this process by retaining all time points together in each step of the resampling and bootstrapping process. The average ERP using this approach is displayed in Figure 4, along with the waveform derived using simple averaging. The time-domain FN component was highly correlated between the two methods ($r(130) = .997$).

2.6 Data Reduction

2.6.1 Time-Domain FN—The time-domain FN component was defined as the maximum negative deflection in the ERP waveform occurring between 26 and 45 sampling bins post-outcome stimulus (or about 203 to 352 ms converted from the 128 Hz sampling rate). This time window was fit to the edges of the FN negative peak in the grand average waveform and is consistent with previous work (Gehring & Willoughby, 2002; Holroyd & Coles, 2002; Miltner et al., 1997). This time range was converted from bins of the 128 Hz resampled signal. For statistical analyses, this component was reduced to a group of 9 electrodes (shown in Figure 3) clustered around Cz. While the FN has traditionally been quantified at FCz, time-frequency analysis has revealed that the FN is composed of fronto-central theta activity and central-parietal delta activity. Thus, 9 electrodes centered around Cz were used due to their location in the middle of these contributing regions.

2.6.2 Time-Frequency evoked power.—To evaluate the time-frequency (TF) phase dynamics related to time-domain ERP signals, TF decompositions were performed upon trial-averaged ERPs. This procedure allows phase-consistent evoked ERP activity to be re-represented in the TF domain, and similar methods have been successfully used to evaluate the relationships between time-frequency activity and time-domain ERPs in a number of other reports (Bernat et al., 2015, 2008; Bernat, Williams, & Gehring, 2005; Bernat, Nelson, et al., 2011; Foti et al., 2015; Harper, Malone, Bachman, & Bernat, 2016; Harper, Malone, & Bernat, 2014; Nelson et al., 2011; Watts et al., 2017). The goal of applying time-frequency analysis to averaged ERPs is to isolate phase-locked activity contributing to the FN, although starting with trial-level versus averaged data is useful for other purposes, including assessing higher frequency activity (Bernat et al., 2007). In the current study, 3rd order Butterworth filters were used to isolate activity within delta and theta frequency ranges, based on the visual inspection of the unfiltered representation of time-frequency energy following the outcome stimulus for one second. A 4 Hz lowpass filter was employed to isolate delta, and a 2 Hz highpass filter in conjunction with a 7 Hz lowpass filter was used for theta. TF decompositions were produced using a binomial reduced interference distribution (RID) variant of Cohen's class of time-frequency transformations upon the full epoch of the filtered signals, using 32 time bins per second and 2 frequency bins per Hz. The RID was chosen to better represent low-frequency activity and avoid smearing the representation of such activity in time (Bernat et al., 2005). Principal component analysis (PCA) was then used separately on each filtered TF decomposition, using a post-stimulus time window of 0–750 ms and a .05–12 Hz frequency window. The TF-PCA data matrix contained TF points as vectors and subject/electrode/trial-averaged scores as rows (a more detailed explanation of this process can be found in Bernat et al., 2005).

Figure 4 displays the grand-averaged TF-PCA decomposition. Four principal components (PCs), explaining 41% of the total variance, were extracted from theta as the best representation of the data. PC1 represented medial frontal theta during the FN, PC2 reflected theta activity after P3, PC3 represented high delta (3 Hz) bilateral occipital activity, and PC4 reflected P2 frontal theta activity. A three PC solution was used as the best representation of delta activity during feedback processing, which explained 68% of the total variance. PC1 reflected low frequency (~1 Hz) slow wave activity, PC2 represented bilateral occipital post-

P3 activity, and PC3 reflected central parietal delta activity (~2 Hz) during the FN time window, also known as the RewP. Theta PC1 and delta PC3 were chosen for further statistical analysis given a priori hypotheses regarding medial frontal theta and central parietal delta activity during the FN time window (see Figure 4). Other PCs were excluded from the analysis because they reflected activity outside of the time range of the FN. The mean PC-weighted TF evoked energy of the two chosen PCs were narrowed down to a subset of 9 electrodes each, shown in Figure 3, with delta clustered around a centro-parietal electrode and theta clustered around a fronto-central electrode. These clusters were selected based on the topographical center of good-bad differences.

2.7 Data Analysis Plan

Three measures were analyzed: FN and TF principal components representing delta and theta. First, each of the three measures was analyzed in separate 2×3 repeated measure ANOVAs of outcome (good vs. bad) by context (gain, even, or loss). A main effect of outcome is expected if theta reflects a context-dependent evaluation of outcomes. An interaction of outcome and context will be seen if delta reflects a combination of context-independent and dependent evaluation of outcomes. Furthermore, this interaction will show the largest delta to good outcomes in the gain context and the smallest in the loss context, and will show little difference in delta across bad outcomes. Additionally, pairwise comparisons will be assessed between outcomes of the same absolute value across context, a necessary comparison for determining context dependence and independence. Finally, multiple regression models with simultaneous entry of predictors will be used to assess the contributions of delta and theta to the FN for each context. Correlations between delta and theta will also be conducted to assess for multicollinearity.

3. Results

3.1 Time-domain FN

Figure 4 displays the average time-domain outcome-locked ERP waveform for the average of nine electrodes (see Figure 3 for electrode locations). The FN is evident as the negative deflection peaking approximately 230 milliseconds after outcome stimulus onset. The scalp distribution of the time-domain FN is parietal, which is common when a difference-wave approach is not used and consistent with delta contributions to the FN.

To test for the effects of outcome (good vs. bad) and context (gain, even, and loss) on the FN, a repeated-measures 2×3 ANOVA was performed. For the FN, Mauchly's Test of Sphericity indicated that the assumption of sphericity had not been violated and the interaction between outcome and context was significant ($F(2,130) = 38.36, p < .001, \eta_p^2 = .23$), where the negative amplitude of the FN scaled with outcome value across the good outcomes and was largest in the loss context (see Figures 4 and 5). Pairwise comparisons revealed that good-bad differences were significant in the gain, even, and loss contexts (gain: $t(131) = 8.86, p < .001, d = .40$; even: $t(131) = 2.87, p = .005, d = .12$; loss: $t(131) = -2.49, p = .01, d = -.12$). Comparisons between contexts revealed a significantly larger good-bad difference in the gain relative to even context ($t(131) = 4.38, p < .001, d = .54$), and in the

even relative to the loss context ($t(131) = 3.77, p < .001, d = .46$). Figure 5 displays the FN mean plot for the relationship between context and outcome.

3.2 Time-frequency

Figure 4 depicts the time-frequency (TF) average waveform and PCA decomposition of the outcome-locked ERPs for theta and delta. The distribution of peak activation is medial frontal for theta and central parietal for delta. Consistent with prior research (Bernat et al., 2015; Bernat, Nelson, et al., 2011) theta activity mirrored the FN in terms of latency and enhanced amplitude to bad relative to good feedback. Furthermore, it is apparent that theta negative polarity activity contributes to enhanced *negative* FN amplitude while positive delta activity contributes to reduced negative amplitude of the FN.

To test for the effects of outcome and context on theta and delta, we again utilized a repeated measures 2 X 3 ANOVA design. For theta, Mauchly's Test of Sphericity indicated that the assumption of sphericity had not been violated and the interaction between outcome and context was significant ($F(2,130) = 26.10, p < .001, \eta_p^2 = .17$). Pairwise comparisons revealed that the gain ($t(131) = -5.65, p < .001, d = -.34$) and even ($t(131) = -5.92, p < .001, d = -.35$) contexts showed significant good-bad differences and the loss context showed no significant difference ($t(131) = .52, p = .60, d = .03$; see Figures 4 and 5). Additionally, comparisons of good-bad difference scores across contexts revealed no significant difference between the gain and even contexts ($t(131) = -.11, p = .91, d = -.01$) but demonstrated significant differences between the gain and loss contexts ($t(131) = -5.14, p < .001, d = -.63$) as well as the even and loss contexts ($t(131) = -5.29, p < .001, d = -.65$). Thus, hypothesis 1a was partially supported, such that theta showed a pattern of context dependence in the gain and even contexts but not the loss context. For delta, a repeated measures 2 X 3 ANOVA with a Greenhouse-Geisser ($\epsilon = .89$) correction revealed a significant interaction between outcome and context ($F(1.78,233.18) = 43.83, p < .001, \eta_p^2 = .25$). Similar to the FN, delta scaled with reward magnitude where a significantly larger good-bad difference was seen in the gain context relative to the even context ($t(131) = 4.72, p < .001, d = .58$), and in the even context compared to the loss context ($t(131) = 3.19, p = .002, d = .39$). Significant good-bad differences were observed in the gain ($t(131) = 10.27, p < .001, d = .55$) and even contexts ($t(131) = 4.58, p < .001, d = .23$) but not in the loss context ($t(131) = .29, p = .77, d = .01$; see Figures 4 and 5). These findings provide strong support for hypotheses 2a and 2b, demonstrating that delta partially reflects context-independent processing.

To test the hypotheses that theta and delta amplitudes would be different between outcomes of the same absolute value across contexts (indicating context-dependence), paired sample t-tests were conducted between the +5 outcomes in the gain and even contexts as well as the -5 outcomes in the even and loss contexts. For theta, both +5 ($t(131) = 4.80, p < .001$) and -5 ($t(131) = 4.30, p < .001$) comparisons were significantly different across contexts, supporting hypothesis 1b and providing more evidence that theta reflects context-dependent processing. For delta, results revealed a significant difference between the +5 outcomes in the gain and even contexts ($t(131) = -7.17, p < .001$) but no difference between the -5 outcomes in the even and loss contexts ($t(131) = -.50, p = .62$). These findings provide

partial support for hypothesis 2c, suggesting that delta partially reflects context-dependence, but only in the gain and even contexts.

3.3 Multiple Regression Models

Multiple regression models predicting the FN with theta and delta, a technique used in previous research (Bernat et al., 2015; Bernat, Nelson, et al., 2011), indicated that delta and theta contributed unique variance to the FN in each context (see Table 2). The relative contributions of delta and theta to the FN were fairly consistent across contexts, and delta accounted for more variance in the FN than theta. No problems with multicollinearity were found (i.e., correlations between delta and theta were non-significant, variance inflation factors were less than 2.0 and tolerance values were greater than .10).

3.4 Correlations

The loss context produced little good-bad differentiation in theta or delta. However, the pattern of results in the gain and even contexts was more consistent with the proposed hypotheses and appear to show meaningful differences between delta and theta in relation to context. Thus, in order to more directly compare context-related processing between delta and theta, we assessed activity in the gain and even contexts alone. Correlations of good-bad differences between the gain and even contexts were calculated for delta and theta separately. Results revealed a large correlation between good-bad differences in the gain versus even contexts for theta ($r(130) = .60, p < .001$) and a small correlation for delta ($r(130) = .17, p = .05$). Steiger's test for the difference between two dependent samples with different variables confirms that these correlations were significantly different ($z = 4.28, p < .001$; Steiger, 1980). These results suggest that outcome processing is highly similar between gain and even contexts in theta, supporting the hypothesis that theta reflects context dependent processing. Alternatively, outcome processing is less related between gain and even contexts in delta, supporting the hypothesis that delta reflects a combination of context-independent and context-dependent processing.

4. Discussion

In the current study, we investigated the role of context in feedback processing by using time-frequency analysis to evaluate ERPs in a modified gambling task. The primary aims were to: 1) assess whether theta reflects context-dependent processing, 2) assess whether delta reflects a combination of context-independent and context-dependent processing, and 3) assess the contributions of theta and delta to the FN and the relationship between context and the FN.

The context dependence versus independence of theta and delta were assessed, where context-dependence was defined as the processing of outcomes in a relative manner within each context, and context-independence was defined as the processing of outcome values in an absolute manner, independent of context (Holroyd et al., 2004). In this study, theta met more criteria for context-dependence and delta met more criteria for context independence. Theta showed similar good-bad differences across the gain and even contexts, suggesting a pattern of context-dependence. These results are consistent with findings suggesting that

theta operates as a binary reflection of good and bad outcomes, where theta is enhanced for the bad outcome (Bernat et al., 2015; Bernat, Nelson, et al., 2011). However, similar good-bad differences were not seen in the loss context, suggesting that theta does not reflect context-dependent processing in a loss-only context. Delta, on the other hand, showed patterns of context independence: activity to good outcomes scaled with reward magnitude and good-bad differences scaled with context valence, such that the largest difference was seen in the gain context and no difference was seen in the loss context. These results are consistent with previous literature indicating that delta, specifically the reward positivity, scales with reward magnitude (Bernat et al., 2015; Proudfit, 2015) and that delta is modulated by more complex, secondary, stimulus characteristics (Bernat et al., 2015; Watts et al., 2017). Delta activity differed between outcomes of the same absolute value in the gain and even contexts, meeting one criterion for context-dependence. Thus, as predicted, delta reflects a combination of context-independent and dependent processing.

While neither delta nor theta showed processing differences in the loss context, good-bad differences were seen in gain and even contexts for both theta and delta. When correlations of good-bad differences in these two contexts were conducted for delta and theta, results revealed that outcome differences between the gain and even contexts were strongly correlated in theta but not in delta. These findings provide further support for the prediction that theta reflects a more binary appraisal of feedback across contexts while delta reflects a more complex evaluation of reward-related feedback.

The importance of evaluating time-domain components using time-frequency analysis is evident by the FN results of the current study. Analysis of the FN revealed a similar pattern to delta, where the FN scaled with the good outcomes across contexts and showed little change in response to the bad outcomes across contexts. Indeed, regression analysis predicting the FN with delta and theta revealed that delta and theta contributed unique sources of variance to the FN across all contexts, but delta accounted for more variance than theta. These results are consistent with previous work showing that the superposition of a slow, positive wave (i.e., delta) during the FN time-window is partially responsible for modulation of the FN (Bernat et al., 2008; Holroyd et al., 2011, 2008; Proudfit, 2015). Consistent with previous work (Holroyd et al., 2004; Nieuwenhuis et al., 2005), no variation in FN amplitude was found between losses in the loss context. Neither delta nor theta was sensitive to varying loss magnitudes, suggesting that both frequencies are contributing the null FN effects in the loss context. Indeed, both delta and theta accounted for unique variance in the FN in the loss context. These findings demonstrate the benefits of using time-frequency measures, as they isolate frequencies that contribute unique variance to time-domain components.

Our findings also indicate that context valence plays a critical role in reward processing. In gain-possible contexts (i.e., the gain and even contexts), good-bad differences scaled positively with context valence (gain > even) for delta and showed binary differences for theta (gain = even). Alternatively, in the context where a gain was not possible (i.e. the loss context), all outcomes were processed similarly in delta and theta (i.e. there were no outcome valence differences, and amplitudes were the lowest of all contexts). Delta and theta did not differentiate outcome valence when all outcomes indicated a loss. Thus, taking

context valence into account may help explain why previous work has showed no differences between varying loss magnitudes in the FN and BOLD signal (Holroyd et al., 2004; Kujawa et al., 2013; Nieuwenhuis et al., 2005). Evidence from the adaptive gain theory may provide support for the importance of context valence (Aston-Jones & Cohen, 2005). The adaptive gain theory (AGT) suggests that when task utility is adequate, participants exploit as much reward as possible (Aston-Jones & Cohen, 2005). Thus, in delta, a moderate good-bad difference is observed in the even context when the option of a small reward exists, and a larger good-bad difference is seen in the gain context when the option of a large reward exists. However, when task utility wanes and becomes less rewarding, participants enter an exploration mode where they disengage from the task at hand and explore alternative means for reward (Aston-Jones & Cohen, 2005). Because participants were given instructions indicating that only loss outcomes were possible in the loss context, perhaps participants disengaged from the task because they knew there was no chance of winning money. Furthermore, because no other rewarding tasks were readily available once disengagement from the loss-only context occurred, participants were not able to explore their environment and find other sources of reward. Thus, disengagement from the task and no alternative means for reward may be responsible for the lack of processing differences between the two loss outcomes.

4.1 Limitations and Future Directions

A context valence explanation for the null effects in the loss context should be explored in future research. For example, are there circumstances in which processing differences are seen between varying loss magnitudes? In a study employing a gambling task with varying loss and gain magnitudes in the same context, delta was sensitive to outcome magnitude but theta was not (Bernat et al., 2015). Thus, when gains occur in the same context as varying loss magnitudes, processing differences are evident in delta. These findings provide further support for the context valence explanation: participants remain engaged in the task when a gain is possible, resulting in processing differences between varying outcome magnitudes. Future work should evaluate the parameters required to detect processing differences to varying loss magnitudes *without* a gain outcome present. For example, is a high magnitude loss more salient when the difference between loss magnitudes is greater (e.g., losing \$100 vs. \$5)? At what magnitude difference does losing less money become motivating for participants to engage in the task?

Additionally, previous work on context dependence has employed an additional level – the breaking even outcome. Our task only contained gains and losses because we wanted each context to purely reflect one type of outcome (e.g., only gains in the gain context). Thus, while this design choice was intentional, the absence of the breaking even outcome in the current study limits the ability to make direct comparisons to previous work.

4.2 Conclusions

The results of the current study indicate that the role of context in reward processing is better elucidated using time-frequency analysis. Theta was more context-dependent and showed a binary response to good-bad differences in the gain and even contexts. Delta was more context-independent: the good outcomes scaled linearly with reward magnitude and good-

bad differences scaled with context valence. The relationship between context and FN amplitude was similar to that of delta, and delta accounted for more variance in the FN than theta. Our findings reveal that theta and delta are differentially sensitive to context and that context valence may play a critical role in determining how the brain processes good and bad outcomes.

5. References

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Figure 1.
Hypothesized relationship between context and outcome for theta and delta.

Figure 2. Sequence of stimulus and outcome events in the reward context gambling task.

Figure 3.
Electrode clusters for analysis of delta (blue), theta (red), and FN (black border).

Figure 4. Time-domain (left column) and time-frequency decomposition (center and right columns) plots of outcome-locked ERPs. The top left plot depicts the unfiltered time-domain waveform across all trials using the subsampling averaging approach, and the plot just beneath it shows the simple averaging approach with no subsampling. FN was quantified as the negative-going deflection between 26–45 bins (~203–352 ms) using peak measurement, as shown by the green vertical lines. The center and right columns show the filtered ERP waveforms and the TF-PCA decompositions for theta and delta activity during the FN window. Rows three through eight display the good vs. bad comparisons for the gain, even,

and loss contexts. Magnitude and direction of regional activity differences are shown by the colored topomaps, and statistical significance is displayed by the gray scale topomaps.

Figure 5. FN, delta, and theta mean plots showing context (gain, even, loss) by outcome (good, bad) relationships. Error bars depict the standard error. The y-axis for delta and theta are PC-weighted means and are thus arbitrary units with respect to microvolts.

Table 1.

Summary of results from three papers on the influence of context on feedback processing.

	Gain Context	Even Context	Loss Context
Holroyd et al., 2004[*]	Best (+5) < Middle (+2.5)	Best (+10) < Worst (−10)	Middle (−2.5) = Worst (−5)
Nieuwenhuis et al., 2005^{**}	Best (+60) > Middle (+30)		Middle (−20) = Worst (−40)
Kujawa et al., 2013[*]	Best (+50) < Worst (+0)		Best (−0) = Worst (−25)

Notes:

^{*} These papers used FN amplitude as the measure of interest; less than signs indicate less negative amplitude

^{**} This paper uses BOLD as the measure of interest.

Table 2.

Multiple regression models of delta and theta predicting FN for each of the three contexts. Standardized beta coefficients are reported. Delta accounts for more of the variance in the FN across contexts.

		Delta		Theta		Overall
		<i>Beta</i>	<i>t</i>	<i>Beta</i>	<i>t</i>	Adj. <i>R</i> ²
FN	Gain	.69	15.84 ***	-.26	-5.92 ***	.50
	Even	.70	15.88 ***	-.18	-4.18 ***	.50
	Loss	.67	14.85 ***	-.26	-5.81 ***	.47

Note:

 $p < .001$