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Examining Neural Activity Related to Pitch Stimuli and Feedback at the Plate: Cognitive and Performance Implications

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This study investigated the relationships among neural activity related to pitch stimuli and task feedback, self-regulatory control, and task-performance measures in expert and novice baseball players. The participants had their event-related brain potentials recorded while they completed a computerized task assessing whether thrown pitches were balls or strikes and received feedback on the accuracy of their responses following each pitch. The results indicated that college players exhibited significantly larger medial frontal negativities to pitch stimuli, as well as smaller reward positivities and larger frontocentral positivities in response to negative feedback, compared with novices. Furthermore, significant relationships were present between college players' neural activity related to both pitches and feedback and their task performance and self-regulatory behavior. These relationships were not present for novices. These findings suggest that players efficiently associate the information received in their feedback to their self-regulatory processing of the task and, ultimately, their task performance.

Keywords: baseball, event-related brain potentials, ERPs, self-regulation, sport performance

In an effort to gain a competitive edge in the game of baseball, some teams, analysts, and researchers have begun to examine hitters' neural activity. These investigations have focused on assessing neural activity associated with classifying different pitch types (Muraskin et al., 2013, 2015; Nakamoto & Mori, 2008, 2012). While this research is insightful in learning the time course and neural structures utilized in pitch recognition processes, these efforts do not account for the influences of pitch decisions and umpire feedback on the subsequent cognitive processes and behavior of hitters throughout a plate appearance. Importantly, we can obtain valuable insight into hitters' cognitive processes, including their inhibitory control, attentional focus, and ability to correct behavior by measuring the dynamic distribution of pitch-by-pitch neural activity rather than looking at each pitch separately. The current study has been designed to address this gap in our knowledge by providing ongoing neural and behavioral measures during a sequence of pitches and performance feedback. By examining neural activity related to pitches and the feedback hitters receive at the plate, we can measure how hitters process all of this information and attempt adjustments to improve their performance.

The initial research examining neural activity during hitting focused on pitch classification (Muraskin et al., 2013, 2015; Nakamoto & Mori, 2008, 2012; Radlo et al., 2001; Sherwin et al., 2012). The intention of these studies was to examine hitters' recognition of different pitch types (Muraskin et al., 2013; Radlo et al., 2001; Sherwin et al., 2012) or hitters' selection of motor responses (Nakamoto & Mori, 2008, 2012). Using a combination of electroencephalogram (EEG) and functional magnetic resonance imaging (fMRI) methodologies, this research showed clear timing and structural signals of neural network activation related to correct versus incorrect pitch classification decisions and suggested patterns of individual differences in neural activation for specific hitters across different pitches (Muraskin et al., 2013). Additional research has shown that expert hitters exert greater inhibitory control during hitting and possess more efficient and effective stimulus–response sets associated with hitting performance (Muraskin et al., 2015; Nakamoto & Mori, 2008, 2012).

While these studies were useful in learning the time course and neural structures utilized by hitters for pitch classification, they did not examine the self-regulatory cognitive processes involved in adjusting at the plate on a pitch-by-pitch basis or the impact correct and incorrect pitch decisions and feedback may have on subsequent hitting behavior. During task execution, one is continually engaged in the real-time self-regulatory monitoring of one's performance. This self-regulatory process, labeled "action monitoring," is utilized to ensure that one's behaviors match the intended outcomes (Gehring & Knight, 2000) and is vital for both goal-directed behavior and learning (Holroyd & Coles 2002). Without this action monitoring process, the cognitive system would not be able to flexibly process ongoing performance feedback and adapt subsequent behaviors to achieve intended outcomes (Yeung et al., 2004).

One way to measure these action-monitoring processes is through event-related brain potentials (ERPs). Event-related brain potentials refer to neural activity measured on the scalp that is time-locked to discrete events (Coles et al., 1990). These ERPs provide continuous millisecond resolution measurement of neural activation throughout a person's engagement with a task. The ERPs are multifaceted, with different ERP components indexing different cognitive processes (Luck, 2005). For hitters in baseball, different action monitoring processes may be engaged during pitch perception compared with those engaged in response to performance feedback from an umpire following a pitch. Furthermore, with their excellent temporal resolution, ERPs can complement neuroimaging measures (fMRI) to provide a broader and deeper understanding of the timing and relationship among neural structures involved in the cognitive processing of task engagement.

Both neural and behavioral indices of action monitoring have been identified, and a recent study examined a number of these

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measures with baseball players (Themanson et al., 2019). In their study, Themanson et al. (2019) examined ERPs in response to performance feedback along with task performance during a pitch classification paradigm in collegiate baseball players and novices. ERPs are necessary to discover the influence of neural activity on task performance in pitch perception, as the entire task of reacting to a baseball happens so quickly that there is no time for a hitter to reliably report what they are thinking during the task. By examining ERPs to performance feedback (feedback-locked ERPs), the researchers were assessing cognitive self-regulatory and learning processes that utilize informational aspects of performance feedback to improve subsequent task performance. The ERP components of interest were the reward positivity (RewP; also referred to as feedback-related negativity [FRN] by Themanson et al., 2019, and others) and the frontocentral positivity (FCP). The RewP is generated by the anterior cingulate cortex (ACC) and reflects a reward prediction error mechanism in the brain that indexes an individual's performance expectations compared with outcomes (Holroyd & Coles, 2002; Holroyd & Yeung, 2012; Krigolson, 2018). The RewP initiates the motor systems in the brain to make self-regulatory adjustments (Baker & Holroyd, 2011; Holroyd & Yeung, 2012) and is sensitive to the difference in value between actual and expected outcomes (Holroyd & Krigolson, 2007). Furthermore, the RewP has been associated with behavioral changes following feedback, including posterror slowing and increased response accuracy (Cohen & Ranganath, 2007; van der Helden et al., 2010; Walsh & Anderson, 2012). The FCP reflects an attentional orienting process (Kok, 2001; Polich, 2007) that redirects attention toward feedback information, is modulated by learning, and has been related to learning and performance outcomes (Arbel & Wu, 2016; Butterfield & Mangels, 2003; Themanson et al., 2019). The FCP has been theorized to indicate greater top–down control of focal attention (Polich, 2007). The researchers found that college baseball players exhibited greater FCP amplitudes to feedback compared with novices, and relationships were present between the RewP amplitude and posterror response accuracy in college players, but not novices. Importantly, this sheds light on the layers of information and processes that can influence a hitter's performance, well beyond what happens during one pitch.

Although the study was important for examining self-regulatory influences on pitch classification processes, it was limited in that the research paradigm used video from a visual perspective behind home plate, not from a more realistic visual perspective in the batter's box. Furthermore, the study did not examine neural activity during the pitches themselves. During pitches, measuring the neural activity related to action monitoring could enhance our knowledge of how mental processes engaged between the pitches and feedback may relate to one another and task performance. By measuring ERPs to pitch stimuli (stimulus-locked ERPs), we can examine ongoing attentional control and inhibitory processes utilized to maintain task-relevant monitoring processes during task engagement. The stimulus-locked ERP components related to action monitoring that occur during the pitches are the N2 and the medial frontal negativity (MFN) components. The N2 indexes response inhibition and conflict monitoring processes during task execution (Clayson & Larson, 2012; Folstein & Van Petten, 2008; Yeung et al., 2004). Similar to the RewP, the N2 is generated by the ACC (van Veen & Carter, 2002) and has been associated with hierarchical reinforcement learning processes (Botvinick et al., 2009; Holroyd & Yeung, 2012). The MFN also originates from the ACC (West, 2003) and is associated with conflict monitoring (Larson et al., 2014; West & Bailey, 2012) and conflict adaptation (West & Alain, 2000). Research has linked the MFN with proactive control sustained throughout task engagement rather than reactive control initiated in response to detected conflict (West & Bailey, 2012).

In the present study, we extend previous research by examining ERPs to performance feedback (RewP and FCP) and measuring ERPs during the pitches themselves (N2 and MFN) while participants complete a pitch-classification paradigm. Additionally, the current study uses the visual perspective of a hitter in the batter's box, making the task more realistic. By examining the dynamic distribution of pitch-by-pitch neural activity and outcomes rather than just looking at each pitch separately, we can obtain valuable insight into hitters' cognitive processes throughout a plate appearance and better understand their self-regulatory adjustments and action monitoring processes, in addition to their ongoing behavior. We may also be able to learn which hitters may be better or worse at utilizing feedback in making their cognitive adjustments at the plate. We hypothesized that college players would exhibit greater N2 and MFN amplitudes compared with novices, suggesting that they engaged in more inhibitory and proactive control during task engagement and extending previous research (Nakamoto & Mori, 2008, 2012). Furthermore, we hypothesized that RewP and FCP amplitudes would be associated with task performance measures for college players, with larger RewP and FCP amplitudes associated with greater posterror performance. These findings would be consistent with previous studies (Arbel & Wu, 2016; Themanson et al., 2019) and would suggest that college baseball players were better able to utilize their feedback processing in an attempt to better learn and improve their performance.

Methods

Participants

Twenty male undergraduate students between the ages of 18 and 22 with little or no organized baseball experience were recruited to participate in this research study. These participants all stopped playing organized baseball before entering high school (age: $M = 18.9$ years, $SD = 1.0$; years of baseball: $M = 5.3$ years, $SD = 3.8$) and were awarded research credit toward a course requirement for their participation in the study. In addition, 15 active Division III collegiate baseball players between the ages of 18 and 22 volunteered to participate in the study (age: $M = 19.4$ years, $SD = 0.9$; years of baseball: $M = 14.7$ years, $SD = 2.0$). These participants received no course credit or compensation for their participation. Participants ($n = 4$) who did not fully complete the study due to computer and equipment difficulties were discarded from the analyses, as were participants ($n = 2$) with excessive noise and artifacts obtained during the ERP data collection, resulting in a final sample size of 29 participants (15 novice college students and 14 collegiate baseball players). All participants reported normal or corrected vision. The study was approved by the institutional review board at the participating institution, and all participants signed an informed consent form indicating their willingness to participate.

Paradigm

After obtaining informed consent, the participants were asked to determine if video recordings of computerized baseball pitches were balls or strikes. The participants sat 1 m in front of a computer monitor and viewed pitches being thrown by a computerized baseball pitcher from the visual perspective of being in the batter's box. The computerized video was recorded using virtual reality software (Big Hit Virtual Reality Baseball, version 1.0.1; Big Hit Games, Seoul, South Korea). Each pitch video was recorded using a virtual reality headset to record the pitch from the visual perspective inside the batter's box. Recordings were made from each batter's box so that the participants could complete the task from a realistic visual perspective based on their handedness while batting (right, left, and switch). The participants were instructed to respond as quickly and as accurately as possible as the pitch was being thrown and the ball was in the air approaching home plate —just like timing a swing decision during an actual plate appearance. The responses were recorded with the participants pressing a button with their left thumb to indicate a ball or with their right thumb to indicate a strike. Each pitch video lasted 1,000 ms, with the video starting as the release of the pitch was occurring; the participants had to respond within 500 ms from the release of the pitch for their response to be recorded. To study the influence of external feedback, visual feedback was given immediately following the conclusion of the pitch video and lasted for 1,000 ms. The feedback indicated whether the participant had made a correct or incorrect ball/strike decision (similar to the nature of umpire feedback). Following the presentation of the feedback, a blank screen was presented for 1,000 ms, and then the next pitch video immediately followed (see Figure 1). The paradigm involves four blocks of 50 pitches each, for a total of 200 pitch trials. The participants saw a random array of six different pitch types (fastball, curve, slider, cutter, sinker, and changeup). Two blocks of the task utilized a right-handed pitcher, while the other two blocks utilized a left-handed pitcher. The four task blocks were counterbalanced across participants. Ball and strike pitches were equiprobable and randomly ordered within each task block.

Behavioral Assessment

The behavioral data were collected for response time (RT; time in ms from the presentation of the pitch stimulus) and response accuracy (i.e., number of correct and error responses) for all trials across task blocks for all participants. In addition to these overall measures, multiple additional behavioral measures of response accuracy and RT were calculated for each participant (Themanson et al., 2014; Themanson et al., 2012; Themanson et al., 2019). These measures utilize the set of error trials for each participant and involve selecting individual correct trials for each participant, without replacement, that matched the RT for each error trial. This matching procedure results in an equal number of matched-correct trials and error trials for each participant to compare differences in postfeedback behavior across accuracy conditions (i.e., posterror behavior vs. postcorrect behavior). For trials immediately following an error trial (posterror trials), and trials immediately following a matched-correct trial (postmatched correct trials), each participant's postfeedback behavior (response accuracy, RT) was calculated as described above. Postfeedback behavior was calculated to examine whether behavioral differences obtained in the present investigation were due specifically to error feedback-related adjustments in cognitive control (e.g., posterror slowing).

Neural Assessment

This study used an EEG to measure ongoing neural activity during the pitching paradigm and created ERPs for each event during the paradigm. The EEG was recorded from 64 sintered Ag–AgCl electrodes embedded in a lycra cap arranged in an extended montage based on the International 10–10 system (Chatrain et al., 1985), with a ground electrode (AFz) on the forehead. The sites were referenced online to a midline electrode placed at the midpoint between Cz and CPz. Vertical and horizontal bipolar electrooculographic activity was recorded to monitor eye movements using sintered Ag–AgCl electrodes placed above and below the right orbit and near the outer canthus of each eye. Impedances were kept below 10 kΩ for all electrodes. A Neuroscan Synamps2 bioamplifier (Compumedics USA Inc., Charlotte, NC), with a 24 bit A/D converter and ±200 mV input range, was used to continuously digitize (500 Hz sampling rate), amplify (gain of 10), and filter (70-Hz low-pass filter, including a 60-Hz notch filter) the raw EEG signal in direct-current mode (763 μV/bit resolution). EEG activity was recorded using Neuroscan Scan software (version 4.3.1; Compumedics USA Inc., Charlotte, NC). Psychology software in Python (PsychoPy, version 1.84.2; Jon Peirce, University of Nottingham, Nottingham, United Kingdom) was used for the stimulus and feedback presentation and to record participant responses.

The ERPs were measured for each event during the paradigm. ERPs possess a superior temporal resolution when compared with functional neuroimaging techniques (fMRI) and can provide valuable insights into the dynamic neural responses to baseball pitches on a millisecond level, which is not possible with fMRI technology (Kappenman & Luck, 2016; Luck, 2005). Offline processing of the ERP components included eye blink correction using a spatial filter (Compumedics Neuroscan, 2003), rereferencing to average mastoids, baseline correction (100-ms time window that runs from −100 to 0 ms prior to the event), band-pass filtering (1–12 Hz; 24 dB/octave; Pontifex et al., 2010), and artifact rejection (epochs with signal that exceeded ±75 μV were rejected). The spatial filter is a multistep procedure that generates an average eye blink, utilizes a spatial singular value decomposition based on principal component analysis to extract the first component and covariance values, and then uses those covariance values to develop a filter that is specifically sensitive to eye blinks and removes those eye blinks (Pontifex et al., 2010; Themanson et al., 2012, 2014, 2019). For feedback-related ERPs, feedback-locked epochs (−100 to 1,000 ms relative to feedback presentation) were created, and for stimulus-related ERPs, stimulus-locked epochs (−100 to 1,000 ms relative to pitch presentation) were created. Average ERP waveforms for correct feedback trials were matched to error feedback trial waveforms on RT and the number of trials to protect against differential artifacts from any stimulus-related activity (Coles et al., 2001). The matching procedure (described above for the assessment of posterror behavior) removes any artifacts that may exist in the timing of ongoing neural processing due to differences in response latency for correct and error trials. This procedure results in an equal number of matched correct trials and error trials for each individual to compare differences across accuracy conditions (Themanson et al., 2012, 2014, 2019). The average number of trials contributing to the ERP waveforms for errors (M = 96.5 trials, SD = 8.0) and matched correct (M = 91.1 trials, SD = 6.5) trials for novices did not differ significantly, $Fs(1, 27) < 2.4$, $ps > .13$, partial η^2 values < .08, from the average number of error (M = 91.9 trials, SD = 7.9) and matched correct (M = 88.1 trials, SD = 6.4) trials for college players. Similarly, the average number of trials contributing to the ERP waveforms for posterror (M = 95.3 trials, SD = 8.6) and postmatched correct (M = 91.0 trials, SD = 4.8) trials for novices did not differ significantly, $Fs(1, 27) < 1.6$, $ps > .22$, partial η^2

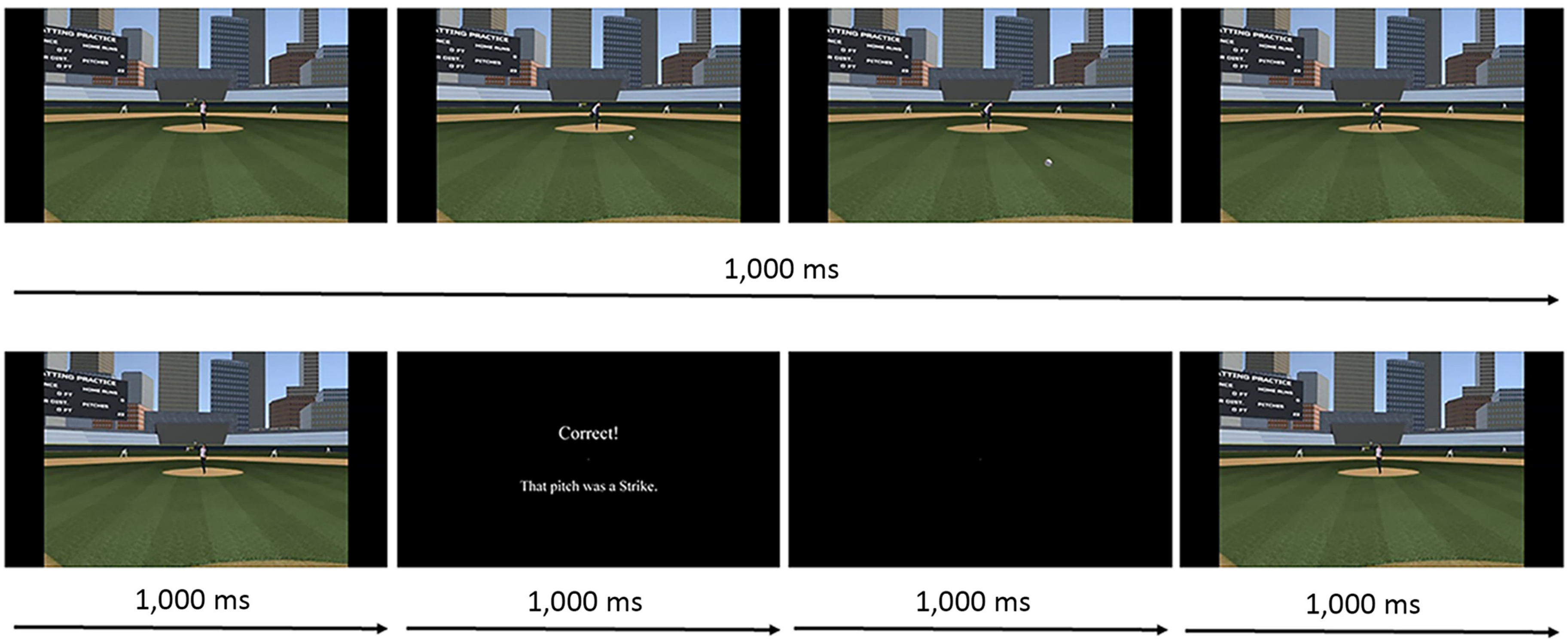

Figure 1 — The top row of images illustrates a visual presentation of pitch stimuli viewed by participants. This figure shows select images from within a pitch video for right-handed batters facing a right-handed pitcher. The entire duration of each pitch video is 1,000 ms. The bottom row of images illustrates the timing of the pitch paradigm. Each pitch video lasted for 1,000 ms, followed by performance feedback presented for 1,000 ms, followed by a blank screen presented for 1,000 ms, followed by the next pitch video, and the pattern continued.

values <.06, from the average number of posterror (M = 91.3 trials, SD = 8.5) and postmatched correct (M = 89.4 trials, SD = 6.4) trials for college players.

For all ERPs, the measurement window parameters were determined by creating overall average waveforms across all task conditions and groups for both the stimulus-locked waveforms and the feedback-locked waveforms (i.e., collapsed localizers; Luck & Gaspelin, 2017). For feedback-locked ERPs, RewP was quantified as the average amplitude between 180 and 280 ms postfeedback in each of two average feedback waveforms (error feedback and matched correct feedback) at FCz, while FCP was quantified as the average amplitude between 300 and 470 ms postfeedback in each of these two average waveforms at FCz. For stimulus-locked ERPs, N2 was quantified as the average amplitude between 200 and 330 ms poststimulus in the average waveform of all pitch stimulus events at FCz. The MFN was quantified as the average amplitude between 300 and 550 ms poststimulus in the average waveform of all pitch stimulus events at FCz. The data for each participant were then outputted into SPSS (version 25.0; IBM Corp., Armonk, NY).

Statistical Analysis

Analyses were conducted using one-way analyses of variance (ANOVAs) to examine the differences in task behavior and neural activity in baseball players and novices. Separate omnibus 2 (feedback type: positive and negative) × 2 (expertise: player and novice) mixed-model ANOVAs were conducted to examine the influence of feedback type and expertise on neural and behavioral measures of self-regulatory action monitoring. Follow-up analyses utilized repeated-measures ANOVAs and two-tailed paired samples t tests with Bonferroni correction as appropriate. The experiment-wise alpha level was set at $p < .05$ for all analyses prior to Bonferroni correction. Bivariate Pearson product–moment correlation analyses were conducted to examine the relationships between the neural and behavioral measures of action monitoring. The Benjamini-Hochberg (1995) correction was calculated for the correlations in order to correct for the false discovery rate given the number of correlations analyzed. With the false discovery rate set at 0.2, due to this being the first study of its kind in the literature (McDonald, 2014), the correction resulted in a p = .04 level of significance for the correlation analyses.

Results

Task Performance

Table 1 provides overall task performance data and postfeedback performance data for each group. The ANOVA for response accuracy revealed that college players performed better than novices, $F(1, 27) = 8.2$, $p = .008$, partial $\eta^2 = .23$, with higher levels of response accuracy for players (M = 49.1% correct, SD = 3.2) compared with novices (M = 46.3% correct, SD = 2.0). The ANOVA for RT did not reveal any significant effect in relation to expertise, $F(1, 27) = 2.0$, $p = .17$, partial $\eta^2 = .07$, with similar RTs for college players (M = 399.6 ms, SD = 50.5) and novices (M = 374.1 ms, SD = 47.2) during the task. These findings speak to the overall greater performance of the players compared with the novices (i.e., no speed accuracy tradeoff), as well as the known difficulty in correctly distinguishing balls from strikes in real time and the severe timing pressure evident during the task. Further evidence for the time pressure comes from the finding of no difference, $t(28) = .82$, $p = .42$, $d = 0.03$, in error RT (M = 379.8 ms, SD = 42.1), and overall RT (M = 378.35 ms, SD = 45.3). In laboratory experiments on other tasks, error RT is typically faster than overall RT, as participants rush to respond before they have processed the stimuli fully (Rabbitt, 1966; Yeung et al., 2004).

Postfeedback Performance

Mixed-model ANOVAs examining postfeedback accuracy as a function of feedback type and expertise revealed a significant effect of expertise, $F(1, 27) = 4.5$, $p = .04$, partial $\eta^2 = .14$, with college players showing overall greater postfeedback accuracy (M = 49.0% correct, SD = 3.8) compared with novice participants (M = 46.6% correct, SD = 2.2). No significant effects were found for feedback type or the interaction between expertise and feedback type, $F\text{s} \leq 1.4$, $p\text{s} \geq .25$, partial η^2 values ≤.05, suggesting the nature of the performance feedback (correct and incorrect) was not associated with alterations in postfeedback task accuracy. For postfeedback RT, the analyses revealed no significant effects for either expertise, feedback type, or their interaction, $F\text{s} \leq 2.1$, $p\text{s} \geq .15$, partial η^2 values ≤.07.

Feedback-Related Neural Measures

Figures 2a, 2b, and 2c provide grand-averaged feedback-locked and stimulus-locked waveforms for each group. The omnibus analysis for the RewP revealed no main effects for either feedback type, $F(1, 27) = 2.8$, $p = .11$, partial $\eta^2 = .36$, or expertise, $F(1, 27) = 0.63$, $p = .43$, partial $\eta^2 = .02$. However, a significant interaction between feedback type and expertise was present, $F(1, 27) = 6.5$,

Table 1 Overall Task Performance (RT and PC), Postfeedback Behavioral Indices (Postfeedback RT and Postfeedback Accuracy), RewP Amplitude, FCP Amplitude, Overall N2, and Overall MFN Amplitude for Baseball Players and Novices, *M* (*SD*)

Variable	Baseball players	Novices
RT	399.7 ms (50.5)	374.2 ms (47.2)
PC	49.1% (3.2)	46.3% (2.0%)
P-EF RT	398.4 ms (50.3)	375.6 ms (49.6)
P-CF RT	401.7 ms (54.6)	370.8 ms (45.7)
P-EF PC	50.4% (4.8)	46.6% (4.5%)
P-CF PC	47.5% (4.6)	46.6% (4.3%)
RewP-EF	3.1 μV (1.9)	2.0 μV (1.8)
RewP-CF	2.9 μV (1.6)	2.9 μV (2.1)
FCP-EF	3.2 μV (1.8)	2.1 μV (2.4)
FCP-CF	3.5 μV (2.4)	3.4 μV (2.4)
N2	−5.5 μV (3.4)	−5.3 μV (3.2)
MFN	−3.8 μV (2.6)	−2.1 μV (1.5)
N2 P-EF	−5.5 μV (3.1)	−5.2 μV (3.3)
N2 P-CF	−5.5 μV (3.7)	−5.4 μV (3.3)
MFN P-EF	−3.9 μV (2.3)	−2.2 μV (1.7)
MFN P-CF	−3.7 μV (2.9)	−2.1 μV (2.0)

Note. RT = response time; PC = percentage correct (response accuracy); P-EF = posterror feedback; P-CF = postcorrect feedback; EF = error feedback; CF = correct feedback; RewP = reward positivity; FCP = frontocentral positivity; N2 = N2 amplitude; MFN = medial frontal negativity.

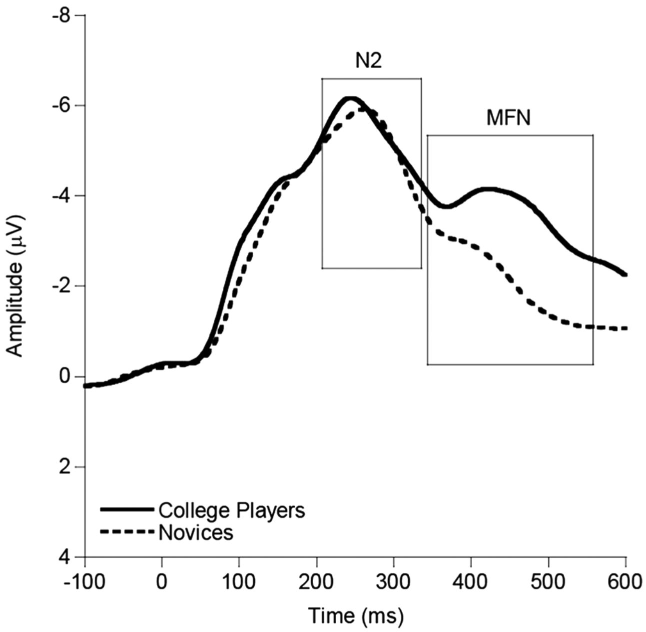

Figure 2a — Grand-averaged stimulus-locked waveforms for all trials by participant group (baseball players and novices) at the FCz electrode site.

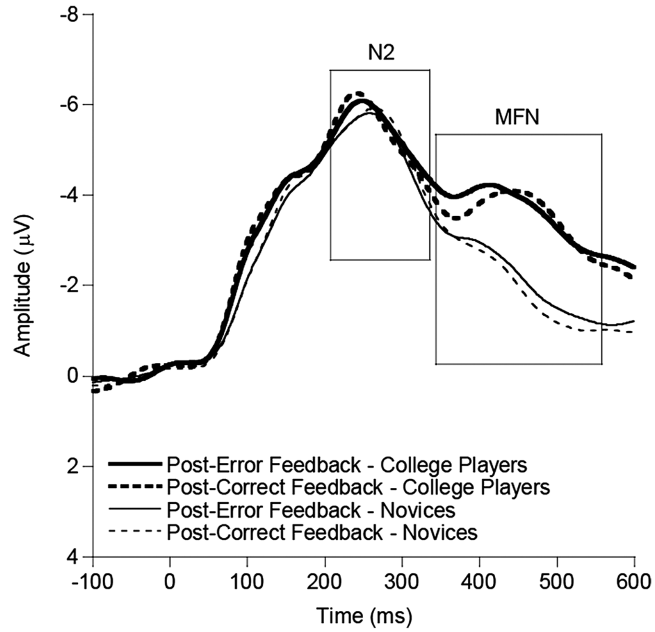

Figure 2c — Grand-averaged stimulus-locked waveforms following error and correct feedback trials by participant group (baseball players and novices) at the FCz electrode site.

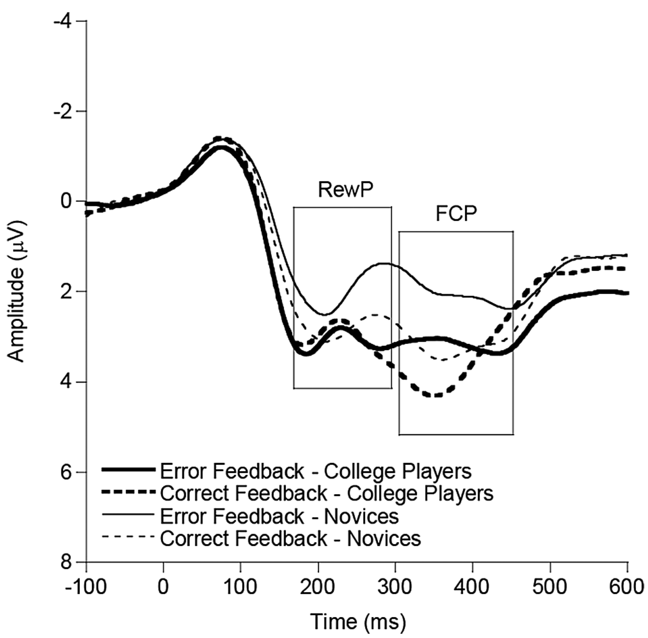

Figure 2b — Grand-averaged feedback-locked waveforms for error and correct feedback trials by participant group (baseball players and novices) at the FCz electrode site.

p = .02, partial η^2 = .19. Follow-up Bonferroni-corrected t tests revealed a significant effect for feedback in novices, $t(14)$ = 2.4, p = .03, d = 0.42, but not in college players, $t(13)$ = .97, p = .35, d = 0.10, with novices showing greater (more positive) RewP activation in response to positive (M = 2.9 μV, SD = 2.1) compared with negative (M = 2.0 μV, SD = 1.8) feedback, whereas college players showed similar levels of RewP activation related to both negative (M = 3.1 μV, SD = 1.9) and positive (M = 2.9 μV, SD = 1.6) feedback.

The omnibus mixed-model ANOVA comparing FCP amplitudes across feedback type and expertise revealed a significant main effect of feedback type, $F(1, 27)$ = 15.5, p = .001, partial η^2 = .36, with correct feedback showing greater (more positive) FCP amplitude (M = 3.4 μV, SD = 2.3) compared with error feedback (M = 2.6 μV, SD = 2.1) across participant groups. No significant main effect was present for expertise, $F(1, 27)$ = 0.6, p = .46, partial η^2 = .02. The significant main effect for feedback type was qualified by a significant interaction between expertise and feedback, $F(1, 27)$ = 5.7, p = .02, partial η^2 = .18. Follow-up Bonferroni-corrected t tests revealed a significant effect for feedback in novices, $t(14)$ = 5.6, p < .001, d = 0.55, but not in college players, $t(13)$ = .9, p = .38, d = 0.15, with novices showing significantly less FCP activation in response to negative (M = 2.1 μV, SD = 2.4) compared with positive (M = 3.4 μV, SD = 2.4) feedback, whereas college players showed similar levels of FCP activation related to both negative (M = 3.2 μV, SD = 1.8) and positive (M = 3.5 μV, SD = 2.4) feedback. These combined findings show that novices exhibited smaller RewP and smaller FCP amplitudes related to negative feedback compared with positive feedback, while experts showed similar RewP and FCP amplitudes related to both negative and positive feedback.

Stimulus-Related Neural Measures

The ANOVA for overall N2 amplitude revealed no significant effect of expertise, $F(1, 27)$ = 0.02, p = .89, partial η^2 = .01, with similar N2 amplitudes for players (M = −5.4 μV, SD = 3.4) and novices (M = −5.3 μV, SD = 3.2). However, the ANOVA for overall MFN amplitude revealed a significant effect, $F(1, 27)$ = 4.3, p = .047, partial η^2 = .14, with college players exhibiting larger (more negative) MFN amplitudes to pitch stimuli (M = −3.8 μV, SD = 2.6) compared with novices (M = −2.2 μV, SD = 1.6).

Relationships Between Neural and Behavioral Measures

Previous research has suggested that RewP and FCP amplitudes are associated with learning and improved task performance during feedback-based learning tasks (Arbel & Wu, 2016; Themanson et al., 2019). Accordingly, we wanted to examine the specific relationships between RewP and FCP amplitudes and postfeedback task performance for college players and novice participants. Bivariate correlations revealed only one significant relationship between RewP, FCP, and postfeedback task performance for novices, with larger (more positive) RewP amplitude following error feedback associated with greater response accuracy following correct feedback for novices, $r = .64$, $p = .01$ (see Table 2 top). No other significant relationships were present in novices.

In baseball players, significant correlations were present between RewP and FCP amplitudes to both correct and error feedback and all measures of postfeedback behavior except response accuracy following correct feedback (see Table 2 bottom). Larger (more positive) RewP amplitudes were associated with faster overall and postcorrect feedback RTs, $rs \geq -.58$, $ps \leq .04$. Furthermore, larger (more positive) RewP amplitudes were associated with greater posterror response accuracy, $rs \geq .59$, $ps \leq .03$. Finally, larger RewP amplitudes were associated with faster RTs, $rs \geq -.58$, $ps \leq .03$, and greater overall response accuracy, $r = .56$, $p = .04$. For FCP amplitudes in baseball players, larger (more positive) FCP amplitudes were associated with faster postfeedback RTs, $rs \geq -.59$, $ps \leq .03$, and greater posterror response accuracy, $rs \geq .59$, $ps \leq .03$. Furthermore, FCP amplitudes related to both error and correct feedback were correlated with overall response accuracy, $rs \geq 59$, $ps \leq .03$, with larger FCP amplitudes associated with greater response accuracy overall, $rs \geq .59$, $ps \leq .03$, and faster overall RT, $rs \geq -.57$, $ps \leq 04$.

Finally, we were interested to see if feedback-locked neural measures were correlated with stimulus-locked neural measures following feedback. No relationships were evident for novices, $rs \leq .36$, $ps \geq .18$ (see Table 3 left). However, a significant relationship was present for college players (see Table 3 right), with larger (more positive) FCP amplitudes related to correct feedback associated with larger (more negative) N2 amplitudes related to pitch stimuli immediately following correct feedback, $r = -.54$, $p = .04$.

Given that the N2 and MFN measure aspects of inhibitory control and proactive control during task execution, we were interested to see if these measures have direct relationships with measures of task performance. Correlations were examined between N2 and MFN amplitudes and measures of task performance (response accuracy, RT). In novices, correlations revealed no significant relationships for the N2 or MFN with either response accuracy or RT, $rs \leq .38$, $ps \geq .16$, suggesting no relationships between stimulus-locked neural measures and task performance. However, in college players, marginally significant relationships

Table 2 Correlations Between Overall Behavior, Postfeedback Behavior, RewP Amplitude, and FCP Amplitude for Novices and College Baseball Players

	RT	PC	P-EF RT	P-CF RT	P-EF PC	P-CF PC
Novices						
RewP-EF	.02	.25	−.05	−.04	−.29	.64*
RewP-CF	.15	.19	.14	.12	.01	.21
FCP-EF	.11	.07	.15	.04	−.18	.43
FCP-CF	.23	−.11	.23	.20	−.30	.39
Baseball players						
RewP-EF	−.58*	.46	−.54	−.61*	.59*	.01
RewP-CF	−.66*	.56*	−.61*	−.69*	.72*	.08
FCP-EF	−.63*	.59*	−.59*	−.65*	.64*	.20
FCP-CF	−.59*	.63*	−.57*	−.58*	.58*	.39

Note. RT = response time; PC = percentage correct (response accuracy); P-EF = posterror feedback; P-CF = postcorrect feedback; EF = error feedback; CF = correct feedback; RewP = reward positivity; FCP = frontocentral positivity.
*$p < .05$ after Benjamini-Hochberg (1995) correction.

Table 3 Correlations Between Feedback-Related and Stimulus-Related Neural Measures for Novices and College Baseball Players

	Novices					Baseball players			
	RewP-EF	RewP-CF	FCP-EF	FCP-CF		RewP-EF	RewP-CF	FCP-EF	FCP-CF
N2	−.09	−.38	−.05	−.17	N2	−.26	−.32	−.32	−.52
MFN	−.10	−.04	−.19	−.22	MFN	.01	−.08	−.17	−.33
N2 P-EF	.02	−.36	.02	−.09	N2 P-EF	−.26	−.33	−.33	−.49
N2 P-CF	−.05	−.36	−.12	−.23	N2 P-CF	−.25	−.32	−.33	−.54
MFN P-EF	−.01	−.02	−.03	−.02	MFN P-EF	−.01	−.09	−.20	−.38
MFN P-CF	−.22	−.07	−.33	−.33	MFN P-CF	.02	−.07	−.15	−.34

Note. P-EF = posterror feedback; P-CF = postcorrect feedback; EF = error feedback; CF = correct feedback; RewP = reward positivity; FCP = frontocentral positivity; N2 = N2 amplitude; MFN = medial frontal negativity.

were present. Specifically, greater (more negative) N2 amplitude was marginally associated with greater response accuracy, $r = -.53$, $p = .05$, and greater (more negative) MFN amplitude was associated with greater response accuracy, but this relationship was marginally significant, $r = -.45$, $p = .10$. When looking at correlations between N2 and MFN amplitudes on trials following correct and error feedback with postfeedback measures of performance, correlations revealed that both greater N2 and MFN amplitudes on stimuli following correct feedback associated with greater response accuracy on those trials, $rs \geq -.57$, $ps \leq .03$. No other correlations were significant between N2, MFN, and postfeedback performance measures, $rs \leq .38$, $ps \geq .16$.

Discussion

The findings of the current study provide evidence for relationships between task performance, neural activity related to pitch stimuli, feedback-related neural activations, and postfeedback task performance during a pitch classification paradigm in college baseball players. This study is the first to examine the relationships among patterns of neural activity related to pitches and feedback and how that pitch-by-pitch neural activity may relate with both task performance and self-regulatory processes during hitting. We found that college players displayed greater proactive control (evidenced by MFN amplitude) with all pitch stimuli, regardless of feedback type, compared with novices. Furthermore, college players showed significant relationships between neural activity and task performance and self-regulatory measures, suggesting that the neural processing of performance feedback and pitch stimuli are related to one another and college players' overall performance and task regulation. Finally, college players exhibited larger RewP and larger FCP amplitudes related to negative feedback compared with novices, suggesting players can more effectively detect and utilize negative feedback and exert greater attentional orienting and focal attention. These findings show the importance of hitters' neural activity throughout their time in the batter's box. By expanding our examination of hitters' neural activity to include pitch-related and feedback-related self-regulatory processes, along with measuring pitch-by-pitch task outcomes, we are able to show a number of significant and meaningful relationships between cognitive processes and task performance during the entire time a hitter is engaged at the plate.

Feedback-Related Self-Regulation

In relation to feedback-related neural activity, previous research has shown larger RewP and larger FCP amplitudes related to negative feedback to be associated with steeper learning curves in feedback-based learning tasks (Arbel & Wu, 2016). Our study extended this finding to include collegiate baseball players in the present task, as college players exhibited larger RewP and larger FCP amplitudes related to negative feedback compared with novice participants, along with greater levels of overall response accuracy during the task. Additionally, smaller RewP and larger FCP amplitudes in baseball players, regardless of the nature of performance feedback (positive/correct, negative/error), were strongly associated with improvements in postfeedback response accuracy and postfeedback RT. These postfeedback behavioral measures of self-regulatory performance monitoring and adjustments reflect reinforcement learning principles (Holroyd & Coles, 2002) and behavioral adaptations during task execution to meet one's intended goals and improve performance (Gehring & Knight, 2000; Kerns et al., 2004; Themanson et al., 2019; Yeung et al., 2004). A larger RewP may reflect that individuals are fast learners who are more efficiently able to extract relevant information from task feedback, and a larger FCP reflects an enhanced ability to orient attention toward informative feedback and improve the learning process, resulting in better performance outcomes (Arbel & Wu, 2016). In our task, collegiate baseball players should be more adept at learning from feedback regarding the strike zone and implementing that feedback in real time to improve performance, compared with novices. Our findings support the notion that the RewP is a proxy for one's task expectations, while the FCP reflects attentional orienting toward task-relevant feedback, and relationships exists between RewP, FCP, and behavioral modifications aimed at improving task performance (Arbel & Wu, 2016; Walsh & Anderson, 2012). Both RewP and FCP amplitudes exhibited significant associations with faster RT and greater response accuracy following each type of performance feedback in baseball players, an effect not seen in novices. By examining these neural measures to feedback, we obtain more objective measures of ongoing cognitive processes and learn insights into task expectations, attentional focus, and self-regulatory processes in baseball players during their time at the plate.

Stimulus-Related Self-Regulation

We observed enhanced MFN amplitudes related to pitch stimuli for baseball players compared with novices, as well as greater overall response accuracy. Furthermore, both enhanced N2 and MFN amplitudes were associated with greater response accuracy and greater response accuracy following correct feedback in baseball players, but not novices. The combined neural and behavioral effects in the present study support the previously noted effects that expert baseball players exhibit greater response inhibition and inhibitory control compared with novices (Nakamoto & Mori, 2008, 2012). The finding of larger MFN amplitudes in college players compared with novices is a novel finding, considering that previous research has not examined the MFN component. Given that the MFN is theorized to measure proactive control during task engagement (West & Bailey, 2012), this finding suggests that baseball players are executing the task under heightened levels of proactive self-regulatory control and conflict adaptation compared with novices. Proactive control is characterized as a preparatory control mechanism aimed at priming and sustaining task-relevant processing pathways before and throughout task engagement in an effort to adapt performance in response to long-lasting (i.e., several seconds or minutes) task-related conflict detected by the ACC (De Pisapia & Braver, 2006). Furthermore, the relationship between response accuracy and MFN amplitude in college baseball players suggests that proactive control may be one mechanism through which baseball players are better able to perform and engage self-regulatory learning compared with novices. Accordingly, highlighting proactive control when working with players may enhance skill acquisition, learning processes, and performance outcomes.

In addition to relationships between overall response accuracy, postcorrect feedback response accuracy, and MFN amplitudes in college players, we also observed significant relationships between postcorrect feedback response accuracy and N2 amplitude in college players. The N2 has been related to the inhibition of action, as well as response conflict (Clayson & Larson, 2012); both processes are present in the current research and postulated to be greater for expert baseball players compared with novices (Nakamoto & Mori, 2008, 2012). The effects of this enhanced response inhibition control are not evidenced in overall larger N2 amplitudes for baseball players compared with novices in the current study, similar to the findings of Nakamoto and Mori (2008, 2012). Rather, the effects of enhanced inhibitory control and response inhibition during task execution can be seen in the relationships N2 amplitude has with overall task performance and postcorrect feedback response accuracy. Inhibitory control, indexed by the N2, is considered vital for behavioral flexibility and the programming and reprogramming of task-relevant action (Mars et al., 2007; Nakamoto & Mori, 2012) during task execution. In baseball players, but not novices, we also discovered a significant relationship between N2 amplitude following correct feedback and FCP amplitude related to correct feedback. Given that FCP is associated with orienting attention toward task feedback to enhance learning (Arbel & Wu, 2016) and that N2 reflects neural processes engaging the inhibitory control of undesired or error responses (Folstein & Van Petten, 2008), this relationship speaks to the potential benefit of college players exhibiting an enhanced ability to correctly adapt and improve performance following feedback. The relationship between feedback processing and response inhibition results in greater overall accuracy and better accuracy following correct feedback for players.

Limitations and Future Directions

The relatively small sample size and the cross-sectional nature of the study each limit the strength of the findings. However, because the findings in the present investigation are consistent with patterns observed in previous research examining self-regulatory processes (Arbel & Wu, 2016; Nakamoto & Mori, 2008, 2012; Themanson et al., 2019), we believe we have assessed reliable associations between neural and behavioral self-regulatory control processes in baseball players while in the batter's box. Furthermore, we have extended and improved upon previous research by examining neural activity related to both pitch stimuli and performance feedback for hitters and providing a baseball-specific task utilizing the more realistic visual perspective from inside the batter's box. Future studies utilizing larger participant samples are warranted, as are study designs that allow for causal inferences and temporal modeling between self-regulatory neural activity and task performance measures.

Conclusions

The current investigation offers new evidence into measures of neural activity related to pitch stimuli and performance feedback during a pitch classification paradigm and the relationships between this neural activity and overall task performance, as well as self-regulatory adjustments in behavior for baseball players. Neural activity related to performance feedback reflects self-regulatory cognitive processes, including performance expectations and attentional orienting. Neural activity during the pitch stimulus itself reflects response inhibition processes and proactive self-regulatory control processes. These processes are associated with learning during task execution, as well as self-regulatory adjustments in motor performance, to improve overall outcomes. These combined results provide evidence for a general self-regulatory framework that is responsive to task-relevant events, including both task stimuli and performance feedback related to task performance. Furthermore, our findings suggest that self-regulatory learning adjustments that exist within this general framework may be associated with enhanced response inhibition and proactive control among baseball players and these inhibitory control processes may be mechanisms underlying hitters' attempts to improve their task performance. Practical implications and uses for this research include assisting and refining player evaluations and player development procedures through a better understanding of feedback-related self-regulatory processes and enhanced proactive control during performance. These cognitive processes vary among individuals, but they can also be trained or improved upon within an individual as well (see Cahn & Polich, 2006; Miltner et al., 1988). Using these neural measures, players, coaches, and trainers can obtain a more objective measure of ongoing cognitive processes present during a plate appearance. These neural data can anchor instructions and conversations that are ongoing between coaches and players. Furthermore, creating a neural profile of a player using this ERP methodology could allow for a longitudinal examination of the player across time, while periodic assessments could monitor patterns of neural activation to implement changes to improve expectations, attention, and control during hitting.

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