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The Influence of Pitch-by-Pitch Feedback on Neural Activity and Pitch Perception in Baseball

Jason R. Themanson,[1] Nicole J. Bing,[1] Brad E. Sheese,[1] and Matthew B. Pontifex[2]
[1]Illinois Wesleyan University; [2]Michigan State University

This study was designed to examine the influence of performance feedback on task performance and neural activity in expert and novice baseball players. Participants completed a video task to determine whether thrown pitches were balls or strikes while their neural activity was recorded. After each pitch, participants were given feedback on the accuracy of their choice. Results indicated that college players exhibited larger frontocentral positivity amplitudes compared with novices, regardless of feedback type. Furthermore, results showed that the feedback-related negativity was related to response accuracy following incorrect feedback for college players, with larger feedback-related negativity amplitude associated with greater response accuracy. This relationship is independent of any relations between overall task accuracy and either feedback-related negativity amplitude or response accuracy following incorrect feedback. These results indicate that the nature of neural activity during pitch feedback for college baseball players can inform and influence participants' subsequent pitch-location performance.

Keywords: anterior cingulate cortex, event-related brain potentials, self-regulation

The scientific examination of batting in baseball has undergone an explosion in recent years, with a number of new paradigms aimed at understanding and exploring both behavioral and neuroscientific influences on batting performance. Although this research has made great strides in developing a better understanding of batting at behavioral, cognitive, and neural levels, a great deal remains unexplored. One notable gap in the literature relates to the measurement of dynamic batting perceptual processes during ongoing pitch-by-pitch sequences and the variables that may influence neural indices underlying those processes. The current research addresses this gap by providing ongoing neural and behavioral measures during a sequence of pitches, to examine the influences of pitch-by-pitch outcomes on subsequent pitch perception.

Previous neuroscientific research has largely examined pitch classification processes (Muraskin, Sherwin, & Shajda, 2013, 2015; Nakamoto & Mori, 2008, 2012; Radlo, Janelle, Barba, & Frehlich, 2001; Sherwin, Muraskin, & Shajda, 2012). These studies examined neural activity during a single pitch, with the intention of examining individual and experiential (expert; novice) differences in batters' capabilities to discern different pitch types (Muraskin et al., 2013; Radlo et al., 2001; Sherwin et al., 2012) or select appropriate motor response sets (Nakamoto & Mori, 2008, 2012). The first study in this area investigated the P300 component of event-related brain potentials (ERPs) and found differences between expert and intermediate batters both in terms of their speed and accuracy in identifying pitch types and in the amplitudes and latencies of their P300 (Radlo et al., 2001), with expert batters more efficiently allocating attention toward perceptual decision-making processes related to pitch classifications. Research has also shown that expert batters exhibit more efficient and effective stimulus-response sets and are more adept at exerting inhibitory control compared with novices (Muraskin et al., 2015; Nakamoto & Mori, 2008, 2012). However, these studies did not clarify the specific timing of the decision events during pitch perception or the neural networks underlying these pitch classification decisions.

Additional research has addressed these issues by examining single-trial patterns of neural activity to different pitch types (Muraskin et al., 2013; Sherwin et al., 2012). This research shows that there are clear signals of neural network activation related to correct versus incorrect pitch classification decisions, and the specific timing of these decisions differs by pitch type and can identify distinct neural profiles for correct pitch classifications compared with incorrect classifications for specific batters across different pitches (Muraskin et al., 2013). Although this research has helped improve our understanding of both the time course and neural structures utilized by batters for pitch classification, it does not examine the impact that feedback may have on subsequent batting behavior. During task execution, making errors or receiving negative feedback leads to increased self-regulatory cognitive control over performance. Cognitive control involves numerous processes that contribute to the "ability to orchestrate thought and action in accordance with internal goals" (Miller & Cohen, 2001, p. 167). One core process within cognitive control is self-regulatory action monitoring or the monitoring of one's behavior to ensure executed actions match intended outcomes (Gehring & Knight, 2000). Action monitoring is crucial for successful learning and the execution of goal-directed behavior (Holroyd & Coles, 2002) and without the coordination of these self-regulatory processes, the human cognitive system would lack the flexibility to process feedback related to performance and adjust subsequent behavior to achieve intended outcomes (Hajcak, Moser, Holroyd, & Simons, 2007; Themanson, Ball, Khatcherian, & Rosen, 2014; Yeung, Botvinick, & Cohen, 2004). Both neural and behavioral indices of action monitoring have been identified.

Themanson, Bing, and Sheese are with the Dept. of Psychology, Illinois Wesleyan University, Bloomington, IL. Pontifex is with the Dept. of Kinesiology, Michigan State University, East Lansing, MI. Themanson (jthemans@iwu.edu) is corresponding author.

One neural index of action monitoring, the feedback-related negativity (FRN), is a negative going deflection in a feedback-locked ERP, which occurs after receiving negative feedback following task execution (Holroyd & Coles, 2002; Miltner, Braun, & Coles, 1997). Source localization and neuroimaging research suggests that the FRN is generated in the anterior cingulate cortex (ACC; Cohen & Ranganath, 2007; Gehring & Willoughby, 2002; Miltner et al., 1997). The FRN reflects a reward prediction error mechanism of the ACC that identifies favorable and unfavorable outcomes (Hajcak et al., 2007; Holroyd & Coles, 2002; Holroyd & Yeung, 2012) and is sensitive to the difference in value between actual and expected outcomes, with a larger FRN amplitude reflecting a larger difference between actual and expected outcomes (Holroyd & Krigolson, 2007; Holroyd, Krigolson, & Lee, 2011; Walsh & Anderson, 2012). Through the dopaminergic reward system, the FRN initiates the motor systems of the ACC to make self-regulatory behavioral adjustments (Baker & Holroyd, 2011; Holroyd & Yeung, 2012). Accordingly, the FRN has been related with two behavioral indicators of cognitive control following negative or incorrect feedback, posterror slowing, and increased response accuracy (Cohen & Ranganath, 2007; van der Helden, Boksem, & Blom, 2010; Walsh & Anderson, 2012).

These two behavioral measures reflect the outcome of self-regulatory action monitoring and provide evidence for the overall recruitment, implementation, and effectiveness of self-regulatory cognitive control. In speeded response tasks, these self-regulatory remedial actions reveal error compensation through a slowing of responses in the following trials (Danielmeier & Ullsperger, 2011) as well as an increased level of response accuracy following error commission (Themanson, Rosen, Pontifex, Hillman, & McAuley, 2012). Moreover, ACC activity on error and high-conflict trials has been directly related to behavioral adjustments on subsequent task trials. These behavioral adaptations have been associated with enhanced prefrontal cortex activation on those same posterror or postconflict trials, which, in turn, has been related back to ACC activation on the previous trial (Kerns et al., 2004). It is believed that action monitoring and the cognitive control of behavior are largely accomplished through interactions between the ACC and the prefrontal cortex (Garavan, Ross, Murphy, Roche, & Stein, 2002; Kerns et al., 2004).

A second neural index of self-regulatory action monitoring is the fronto-central positivity (FCP) that occurs in response to feedback (Arbel, Goforth, & Donchin, 2013; Arbel, Hong, Baker, & Holroyd, 2017). The FCP, also termed the P3a (Butterfield & Mangels, 2003; Themanson et al., 2015), has been associated with the selection of stimulus information through attentional orienting (Knight, 1984; Kok, 2001; Rushby, Barry, & Doherty, 2005). This orienting process reflects the disengagement of a previous attentional focus toward a reengagement of attentional processes elsewhere (Squires, Squires, & Hillyard, 1975). Accordingly, the FCP is sensitive to feedback and self-regulatory processes, but it is not unique to these types of processes. FCP amplitude has been related to valence and learning outcomes in some research (Arbel et al., 2013, 2017; Butterfield & Mangels, 2003) and has been theorized to index attentional orienting with increased amplitude indicating greater top-down control of focal attention (Polich, 2007).

The current study was designed to assess the neural and behavioral indicators of self-regulatory action monitoring processes while batters viewed and responded to pitch videos and received feedback. Previous work examining the use of video-based training for perceptual-cognitive decision-making tests has established the validity and reliability of the type of protocol used in the present investigation (Larkin, Mesagno, Spittle, & Berry, 2015). By examining the distribution of pitch-by-pitch outcomes rather than just looking at each pitch separately, we can obtain insight into batters' neural activity between pitches and better understand their decision-making processes and pitch-by-pitch responses at the plate. Based on research findings that suggest experts exhibit more efficient and effective attentional and control processing during pitch classification tasks, we predict experts (i.e., college-level players) will exhibit enhanced sensitivity and reactivity to negative feedback compared with novices. This enhanced sensitivity will be evidenced in both larger FRN amplitude to negative feedback and greater performance accuracy following negative feedback compared with novices. Furthermore, experts will exhibit greater FCP amplitudes following all performance feedback, regardless of feedback type, indicating a greater degree of attentional allocation to feedback stimuli compared with novices. With the performance experience of experts and the time constraints of the task, we predict that experts will be more capable to utilize the feedback they receive and enhance posterror response accuracy without exhibiting the posterror slowing evidenced by nonexperts in other task environments.

Methods

Participants and Pitching Paradigm

A total of 33 male undergraduate students aged between 18 and 22 years with no organized baseball experience were recruited to participate in this study. These participants were awarded research credit toward a class requirement, but no other compensation was provided. In addition, 27 active Division III collegiate baseball players aged between 18 and 22 years volunteered to participate in the study. Participants ($n = 3$) who did not fully complete the study because of computer and equipment difficulties were omitted from the analyses as were participants ($n = 3$) with excessive noise and artifacts obtained during ERP data collection, resulting in a sample size of 54 participants (29 novices and 25 collegiate baseball players). All participants reported normal or corrected vision. The study was approved by the institutional review board at Illinois Wesleyan University, and all participants signed an informed-consent form indicating their willingness to participate.

Participants were asked to determine if video recordings of baseball pitches were balls or strikes. Participants sat 1 m in front of a computer monitor and viewed pitches being thrown by real baseball pitchers from the perspective behind home plate (Muraskin et al., 2015; Sherwin et al., 2012) similar to a catcher or umpire viewpoint. They were told that their response process should occur as the pitch is being thrown and the ball is approaching home plate—just like timing a swing decision during an actual plate appearance. Responses were recorded by pressing a button with their left thumb indicating a ball or with their right thumb indicating a strike. Each pitch video lasted 3,000 ms, with the release of the pitch occurring at 2,000 ms (to allow for the participant to view the pitcher's wind up prior to releasing the pitch through the completion of the pitch), and the response window closing at the end of the video clip (allowing a 1,000-ms response window). 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). The presentation of the next pitch video immediately followed the conclusion of the feedback. The pitching paradigm involves five blocks of 20 pitches each for a total of 100 pitch trials. There were 10 unique pitch videos used from each of 10 different pitchers (seven right-handed and three left-handed) for the 100 pitch trials in the task with a ball/strike probability of 50% for each pitcher and for the task overall. The pitches utilized in the videos included fastballs as well as curveballs and changeups.

Behavioral Assessment

Behavioral data were collected on response time (RT) and response accuracy for all trials across task blocks. Multiple additional behavioral measures of accuracy and RT were calculated for each participant (Themanson et al., 2012, 2014). Specifically, these measures were calculated for (a) trials following an incorrect feedback trial (posterror trials) and (b) trials following a subset of correct trials matched to specific incorrect trials based on RT (postmatched-correct trials). Each participant's posterror behavior (accuracy and RT) was compared with his postmatched-correct behavior to examine whether behavioral differences obtained in the present investigation were due specifically to incorrect feedback-related adjustments in cognitive control.

Neural Assessment

This study used an electroencephalogram (EEG) to measure ongoing neural activity during the pitching paradigm and created ERPs for each event during the paradigm. ERPs refer to neuroelectric activity measured on the scalp that is time-locked to discrete events and represents brain activity in response to or in preparation for a stimulus or response. ERPs possess a superior temporal resolution when compared with functional neuroimaging techniques and can provide valuable insights into the dynamic neural responses to baseball pitches on a millisecond-to-millisecond level that are not possible with fMRI technology. The EEG was recorded from 64 sintered Ag–AgCl electrodes embedded in an elastic cap (Compumedics USA Inc., Charlotte, NC) arranged in an extended montage based on the International 10–10 system (Chatrain, Lettich, & Nelson, 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.,), with a 24-bit analog-to-digital converter and ±200 mV of input range, was used to continuously digitize (sampling rate of 500 Hz), 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 4.5.1; Compumedics USA Inc.,). PsychoPy (version 1.84.2; Peirce, 2009) was used for stimulus presentation and to record participant responses during the pitching paradigm.

Offline processing of the ERP components included eyeblink correction using a spatial filter (Compumedics Neuroscan, 2003); rereferencing to average mastoids; creation of response-locked epochs (−100 to 1,000 ms relative to feedback onset); baseline removal (100 ms time window that runs from −100 ms to 0 ms prior to the event); band-pass filtering (1–12 Hz; 24 dB/octave); and artifact rejection. Epochs with signals that exceeded ±75 µV were rejected. Average ERP waveforms for correct feedback trials were matched to incorrect feedback trial waveforms on RT and number of trials to protect against differential artifacts from any stimulus-related activity (Coles, Scheffers, & Holroyd, 2001). This procedure removes any artifacts that may exist in the timing of ongoing neural processing due to differences in response latency for correct and incorrect trials and results in an equal number of matched-correct feedback trials and incorrect feedback trials for each individual to compare differences across accuracy conditions (Themanson et al., 2012, 2014). FRN was quantified as the average amplitude between 150 and 250 ms postfeedback in each of these two average waveforms (incorrect feedback and matched-correct feedback) at the frontocentral midline electrode site (FCz) while FCP was quantified as the average amplitude between 300 and 450 ms postfeedback in each of these two average waveforms at FCz.

Statistical Analysis

Analyses were conducted using one-way analyses of variance (ANOVAs) to examine the differences in behavior in college players and novices. Separate omnibus 2 × 2 (Feedback type [positive, negative] × Expertise [college player, 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 relationship between the neural and behavioral measures of action monitoring, and hierarchical linear regression analyses were conducted to examine whether FRN accounted for a significant proportion of the variance in the behavioral indices of action monitoring (postfeedback accuracy and RT). Overall response accuracy was included as a covariate in the first step of the hierarchical linear regression analyses given its covariation with the dependent measure (Miller & Chapman, 2001). In the second step, FRN amplitude was added as a predictor. Goodness-of-fit of the model was considered in terms of variance explained by the model, expressed as R^2. The increase in variance explained by the models was tested for significance after each step.

Results

Task Performance

Table 1 provides overall task performance data as well as postfeedback performance data. As expected, college players performed better than novices, $F(1, 52) = 30.1$, $p < .001$, $\eta_p^2 = .37$, with higher levels of response accuracy ($M = 64.3\%$ correct, $SD = 9.0$) compared with novices ($M = 52.7\%$ correct, $SD = 6.5$). However, no significant differences were present in relation to RT, $F(1, 52) = 3.3$, $p = .07$, between college players ($M = 564.0$ ms, $SD = 104.9$) and novices ($M = 513.7$ ms, $SD = 97.2$). The experts did respond a bit more slowly than novices, potentially due to the efficiency in their batting swing processes, which allows a greater duration of time for them to engage their pitch perception processes before initiating action, but again, these differences were not statistically significant. Taken together, these findings show the college players' familiarity and expertise with the task compared with novices but also demonstrate the known degree of difficulty in

Table 1 Overall Task Performance (RT, %Correct), Postfeedback Behavioral Indices (Postfeedback RT and Postfeedback Accuracy), FRN Amplitude, and FCP Amplitude by Feedback Type (Correct and Incorrect) for College Players and Novices, *M* (*SD*)

Variable	College player	Novice
Overall RT	564.0 ms (104.9)	513.7 ms (97.2)
Overall PC	64.3% (9.0)	52.7% (6.5)
Postincorrect feedback RT	555.2 ms (99.4)	520.7 ms (109.6)
Postcorrect feedback RT	571.0 ms (101.3)	515.1 ms (94.3)
Postincorrect feedback PC	64.8% (11.7)	52.6% (11.0)
Postcorrect feedback PC	62.2% (14.8)	51.1% (8.6)
FRN—incorrect feedback	2.3 µV (3.3)	2.1 µV (2.8)
FRN—correct feedback	2.7 µV (2.8)	2.9 µV (2.9)
FCP—incorrect feedback	3.9 µV (4.4)	1.3 µV (3.2)
FCP—correct feedback	4.5 µV (3.5)	3.3 µV (3.5)

Note. RT = response time; PC = percentage correct (response accuracy); FRN = feedback-related negativity; FCP = frontocentral positivity.

properly discerning balls from strikes as they are thrown. In terms of RT, the findings showing no differences between college players and novices speak to the timing pressures evident during a pitch location task. Further evidence for this is the finding of no difference, $t(53) = 1.2$, $p = .22$, in overall RT ($M = 537.0$ ms, $SD = 103.0$) and error RT ($M = 533.1$ ms, $SD = 95.3$). 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; Ridderinkhof, Ullsperger, Crone, & Nieuwenhuis, 2004; Yeung et al., 2004). In this task, participants are always under time pressure due to the severe time limitations inherent within the task itself, leading to no differences between overall and error RT.

Postfeedback Performance

Mixed-model ANOVAs examining postfeedback performance (accuracy; RT) as a function of feedback type and expertise revealed a significant effect of expertise, $F(1, 52) = 20.6$, $p < .001$, $\eta_p^2 = .28$, with college players showing greater postfeedback accuracy ($M = 63.5\%$ correct, $SD = 13.2$) compared with novice participants ($M = 51.9\%$ correct, $SD = 9.4$). No significant effects were found for feedback type, $F(1, 52) = 1.2$, $p = .28$, or the interaction between expertise and feedback type, $F(1, 52) = .1$, $p = .77$, suggesting the nature of the performance feedback (correct; incorrect) was not associated with alterations in postfeedback task accuracy during the task.

For postfeedback RT, analyses revealed no significant main effects for either expertise, $F(1, 52) = 2.8$, $p = .10$, or feedback type, $F(1, 52) = 1.0$, $p = .33$. However, a significant interaction effect was present, $F(1, 52) = 4.4$, $p = .04$, $\eta_p^2 = .08$, indicating that postfeedback RT was slower following incorrect feedback ($M = 520.7$ ms, $SD = 19.5$) compared with correct feedback for novices ($M = 515.1$ ms, $SD = 18.1$) but was faster following incorrect feedback ($M = 555.2$ ms, $SD = 21.0$) compared with correct feedback ($M = 571.0$ ms, $SD = 19.5$) for experts. Follow-up Bonferroni-corrected *t* tests showed a significant time effect for college players, $t(24) = 2.3$, $p = .02$, and no significant effect for novice participants, $t(28) = .73$, $p = .47$, indicating that the college players showed a significantly faster posterror RT compared with postcorrect RT while the novices showed no significant difference. These findings, when combined with the postfeedback response accuracy findings, suggest college players are more efficient (i.e., improved) in their task performance following incorrect feedback than following correct feedback (same response accuracy; faster RT). For novices, these findings suggest the nature of the feedback (correct; incorrect) was not directly associated with any alterations in postfeedback task performance, providing evidence that novices were not able to successfully engage self-regulatory processes following performance feedback to improve subsequent task performance.

Neural Measures of Action Monitoring

A mixed-model ANOVA comparing FRN amplitudes across feedback type and expertise revealed a significant main effect of feedback type, $F(1, 52) = 4.6$, $p = .04$, $\eta_p^2 = .08$, with incorrect feedback showing greater FRN amplitude ($M = 2.2$ µV, $SD = 3.0$) compared with correct feedback ($M = 2.8$ µV, $SD = 2.9$) across participant groups. No significant effects were present for expertise, $F(1, 52) = .01$, $p = .93$, or the interaction between expertise and feedback type, $F(1, 52) = .6$, $p = .45$, suggesting participants' expertise in baseball was not associated with alterations in FRN in this task.

A mixed-model ANOVA comparing FCP amplitudes across feedback type and expertise revealed a significant main effect of feedback type, $F(1, 52) = 17.2$, $p < .001$, $\eta_p^2 = .25$, with correct feedback showing greater (more positive) FCP amplitude ($M = 3.8$ µV, $SD = 3.5$) compared with incorrect feedback ($M = 2.5$ µV, $SD = 4.0$) across participant groups. In addition, a significant main effect was present for expertise, $F(1, 52) = 4.1$, $p = .04$, $\eta_p^2 = .07$, with college players showing greater (more positive) FCP amplitude ($M = 4.2$ µV, $SD = 4.0$) compared with novices ($M = 2.3$ µV, $SD = 3.4$) regardless of feedback type. These effects were qualified by a significant interaction between expertise and feedback, $F(1, 52) = 5.3$, $p = .03$, $\eta_p^2 = .09$. Follow-up Bonferroni-corrected *t* tests revealed a significant effect for feedback in novices, $t(28) = 5.2$, $p < .001$, but not college players, $t(24) = 1.2$, $p = .26$, with novices showing significantly less FCP activation in response to negative feedback ($M = 1.3$ µV, $SD = 3.2$) compared with positive feedback ($M = 3.3$ µV, $SD = 3.5$), whereas college players showed similar levels of FCP activation to both negative ($M = 3.9$ µV, $SD = 4.4$) and positive ($M = 4.5$ µV, $SD = 3.5$) feedback. Figure 1 provides ERP waveforms by participant expertise and feedback type, highlighting the observed differences in FRN and FCP amplitudes.

Relationship Between Neural and Behavioral Measures

Given that previous research has suggested that FRN amplitudes are associated with learning and improvements in task performance following incorrect or negative feedback (van der Helden et al., 2010; Walsh & Anderson, 2012), we wanted to examine the specific relationship between FRN amplitude and postincorrect feedback task performance for college players and novice participants. Bivariate correlations revealed a significant relationship between FRN amplitude and postincorrect feedback response accuracy for college players, $r = -.55$, $p = .004$, but not novices ($r = -.01$, $p = .96$; see Tables 2 and 3 for correlations), with larger (more negative) FRN amplitudes associated with greater

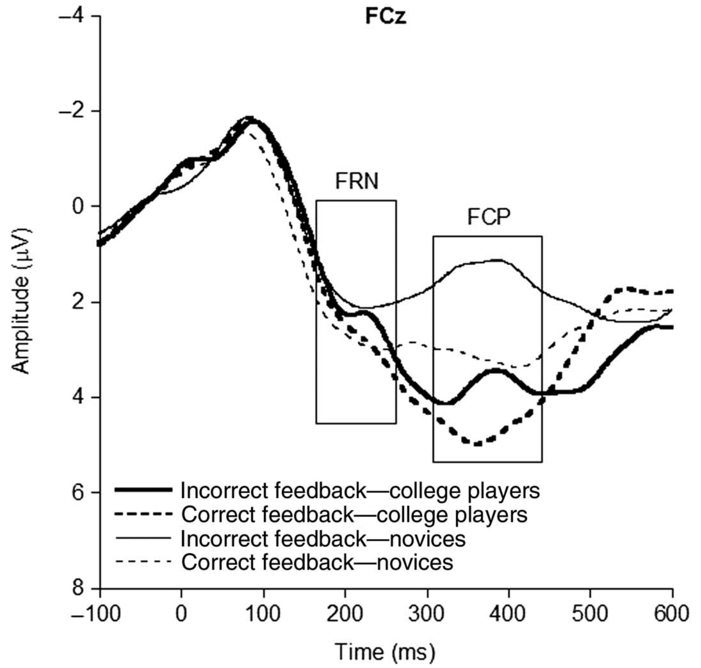

Figure 1 — Grand-averaged feedback-locked waveforms for incorrect and correct feedback trials for both college players and novices at the FCz electrode site. FRN = feedback-related negativity; FCP = frontocentral positivity.

Table 2 Correlations Between Overall Behavior, P-IF Behavior, and FRN Amplitude Following Incorrect Feedback for College Players

	1	2	3	4	5
1. RT	—				
2. PC	.68**	—			
3. P-IF RT	.97**	.56**	—		
4. P-IF PC	.59**	.74**	.59**	—	
5. FRN-IF	−.11	−.36	−.10	*−.55**[a]*	—

Note. RT = response time; PC = percentage correct (response accuracy); P-IF = postincorrect feedback; FRN = feedback-related negativity.

[a]There was a relationship between neural measures (the FRN) and behavioral measures (P-IF PC).

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

Table 3 Correlations Between Overall Behavior, P-IF Behavior, and FRN Amplitude Following Incorrect Feedback for Novices

Variable	1	2	3	4	5
1. RT	—				
2. PC	.61**	—			
3. P-IF RT	.98**	.55**	—		
4. P-IF PC	.51**	.73**	.40*	—	
5. FRN-IF	−.02	−.04	.01	−.09	—

Note. RT = response time; PC = percentage correct (response accuracy); P-IF = postincorrect feedback; FRN = feedback-related negativity.

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

postincorrect feedback accuracy. To assess the unique relationship between FRN and postincorrect feedback response accuracy in college players, a hierarchical linear regression analysis was conducted regressing postincorrect feedback response accuracy on overall response accuracy, entered in the first step, and FRN amplitude, entered separately in the second step. The regression model was significant, $R^2 = .79$, $F(2, 22) = 19.4$, $p < .001$, with both a significant effect for overall response accuracy in the first step, $R^2 = .54$, $F(1, 23) = 27.2$, $p < .001$, and a significant FRN amplitude influence in the second step, $\Delta R^2 = .10$, $F(1, 22) = 5.8$, $p = .02$. This finding suggests that larger (more negative) FRN amplitude following incorrect feedback was associated with better postincorrect feedback response accuracy for college players independent of the relationship between overall response accuracy and postincorrect feedback response accuracy for college players (see Table 4 for a summary of this regression analysis and Figure 2 for a scatterplot of

Table 4 Summary of the Regression Analysis for Variables Predicting Postincorrect-Feedback Accuracy

Variables	*B*	*SE B*	*β*
Step 1			
Overall percentage correct	.96	.18	.74**
Step 2			
Overall percentage correct	.81	.18	.62**
Feedback-related negativity	*−1.2*	*.48*	*−.33**

Note. *B* = the unstandardized beta value (or the slope of the regression line); *SE* = standard error. Italic values denote the instances of a relationship between neural measures (the FRN) and behavioral measures (P-IF PC).

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

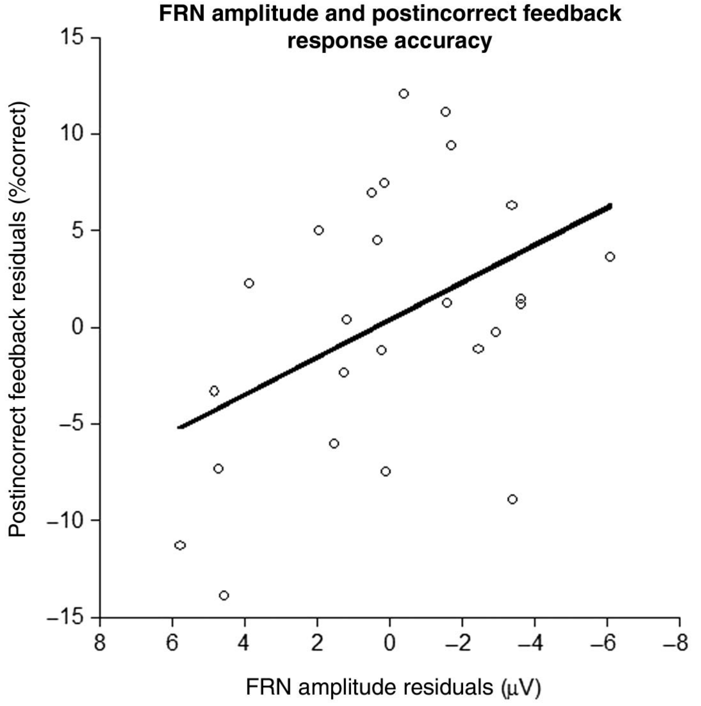

Figure 2 — Scatterplot for the relationship between residuals in FRN and postincorrect feedback response accuracy for college players after controlling for the influence of overall response accuracy. FRN = feedback-related negativity.

this relationship). No relationships were present between neural activity and measures of postfeedback RT.

Discussion

The current research provides evidence for a relationship between feedback-related neural activations and subsequent performance during a pitch location paradigm. This study is the first to examine the dynamic relationships among pitch-by-pitch outcomes and how feedback may influence the skill acquisition process and batters' behavior. In particular, we found that college players exhibited greater attentional orienting and focal attention (indexed by FCP amplitude) to feedback stimuli across both feedback types compared with novices, suggesting greater attentional focus toward acquiring a more accurate working representation of the strike zone. Furthermore, college players exhibited a beneficial relationship between FRN amplitude following incorrect decision feedback and postfeedback performance, with larger FRN amplitudes associated with greater postfeedback response accuracy. This relationship was independent of the relationship between overall response accuracy and postfeedback accuracy and was only present for college players. These data suggest that larger FRN amplitudes may be related to an enhanced ability to adapt during a plate appearance for college players and to improved pitch-location processes. When combined, these current findings speak not only to the importance of expanding our examination of batters' neural activity to include self-regulatory attentional processes and pitch-by-pitch outcomes but also to the nature of how these self-regulatory processes interact with skill acquisition and improved task performance. Finally, these findings speak to the important role of immediate feedback (Dickey, 2005) in task implementation and instructional design methodologies for both novices and experts.

Our data show a relationship between FCP amplitudes, feedback types, and expertise, with larger (more positive) FCP amplitudes for college players compared with novices regardless of feedback type and larger FCP amplitudes for novices in response to correct feedback compared with incorrect feedback. The finding of larger FCP amplitudes for college players may reflect a greater degree of orienting attention and attentional focus (Butterfield & Mangels, 2003; Kok, 2001; Polich, 2007) toward feedback in an attempt to better acquire (Arbel et al., 2013, 2017) accurate representations of the strike zone. Typically, FCP amplitudes are larger following negative feedback (Arbel et al., 2013, 2017); however, research has shown that the FCP can also be influenced by confidence (Butterfield & Mangels, 2003) and the informational value of feedback (Arbel et al., 2013). Given the difficult nature of the present task, with the unclear definition of what is a strike/ball as defined by the umpire, all feedback types are informative toward the task. Accordingly, attending equally to all feedback, as seen in the college players, would be advantageous toward improving within the task. Meanwhile, the lack of FCP in response to negative feedback, as seen in novices, would suggest novices lack appropriate self-regulatory attentional processing toward improving performance in this task. Given that properly discriminating between pitches is more valuable for active collegiate baseball players compared with novices, it could also be that novices simply were not as motivated or goal-directed during the task compared with experts. This difference in task-relevant motivational importance could also explain some of the differences in FCP findings between experts and novices in our study.

In addition, greater FRN amplitude in response to incorrect feedback was associated with improvements in response accuracy following incorrect feedback for college players. This is consistent with previous FRN research (van der Helden et al., 2010; Walsh & Anderson, 2012) as well as theories that conceptualize the FRN as an index of a reward prediction error mechanism (Holroyd & Coles, 2002; Holroyd & Yeung, 2012) that identifies favorable and unfavorable outcomes, is sensitive to differences between actual and expected outcomes (Holroyd & Krigolson, 2007; Holroyd et al., 2011), and signals to initiate motor systems and self-regulatory adjustments (Baker & Holroyd, 2011; Holroyd & Yeung, 2012). As with the FCP findings, this effect was only present in the college players, suggesting the novices did not properly engage self-regulatory processes aimed at skill acquisition and improving on the task following incorrect feedback. This lack of an effect in novices may be due to their difficulty with the task. Novices performed just over chance levels (50%), which may speak to their inability to recruit self-regulatory resources following incorrect feedback as they would be largely unaware of how to effectively improve their performance and what strategies could be implemented on subsequent task trials. FRN amplitudes are typically larger in response to negative or incorrect feedback. However, with difficult tasks, like the one in the current study, FRN amplitudes can be similar across feedback types, or even larger for positive feedback (Holroyd & Krigolson, 2007; Oliveira, McDonald, & Goodman, 2007), reflecting sensitivity to one's outcome expectations. Regardless of one's expectations, the relationship between FRN amplitude and behavioral modifications aimed at improving subsequent task performance is robust across the literature (Walsh & Anderson, 2012) and present for college players, but not novices, in the current study.

Limitations

The current study utilized a behind-the-plate perspective in the task, and participants viewed the videos on a small screen from a short distance. This distorted the visual angle and optic flow of the task as well as aspects of the temporal decision-making processes and time to respond within our task compared with hitting a baseball in real life. We endeavored to maximize internal validity, consistency, and control in our paradigm, but these decisions reduced the ecological validity in our study. We would not expect increased ecological validity to alter the main findings from the study regarding the utility of examining self-regulatory neural activity in baseball hitters and the relationship between self-regulatory neural activity and experts' enhanced ability to use negative feedback for the purposes of enhancing response accuracy on the subsequent pitch. However, this will remain an empirical question until it is explicitly tested. Accordingly, future studies should utilize a more realistic task environment (a batter's box perspective, presenting the videos to participants on a large screen from a longer distance) to better approximate the perceptual and cognitive processes ongoing during an at bat and to prevent any disruptions to the actual task of making pitch location decisions during an at bat. Furthermore, future research should investigate individual differences to uncover potential moderators of the neural and behavioral associations present between self-regulatory and pitch location processes.

Conclusions

Our results suggest that neural activity in response to pitch feedback can influence batters' performance on subsequent pitches, and specific patterns of neural activity are associated with improved performance on a pitch location task for expert performers (college players), but not novices. This provides a clearer understanding of what self-regulatory processes are engaged during an at bat as the dynamic nature of external feedback and information informs a batter's skill-acquisition process over the course of repeated pitches. Furthermore, we showed that expertise interacts with attentional processes and types of information throughout the course of an at bat, with experts showing greater degrees of self-regulatory attentional allocation and focus, with neural activity related to improved postfeedback performance, for college baseball players but not baseball novices. Given that a vast majority of plate appearances involve multiple pitches and an ongoing dynamic between batters and the feedback they receive in real time throughout their at bats, the current study informs the process of how batters utilize the informational feedback they receive to adapt and improve their subsequent performance.

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