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ORIGINAL RESEARCH

The Relationships Between Neural Activity and In-Game Hitting Performance in Baseball

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The current study examines the relationships between hitters' neural activity and their in-game hitting performance. Collegiate baseball players completed a computerized video task assessing whether thrown pitches were balls or strikes while their neural activity was recorded. In addition, each player's hitting statistics were collected for the following baseball season. Results showed that neural activity during the computerized task was associated with in-game hitting performance, even after accounting for other individual difference variables. These findings indicate that players' neural activity measured in a laboratory environment shows a translational relationship with in-game hitting performance over time. Neural activity provides a more objective analysis of players' ongoing self-regulatory processes during hitting and a better understanding of the cognitive processes associated with hitting performance. Self-regulatory cognitive control is adaptable and trainable, and this research advances the measurement of cognitive variables related with in-game hitting performance in baseball.

Keywords: event-related brain potentials, ERPs, self-regulation, inhibitory control, proactive control, sport performance

Baseball has seen tremendous advancements in the application of technology and information processing in recent years. From high-speed cameras, LiDAR, force plates, and motion capture to a myriad of advanced statistical models, baseball is working to gather more objective and exacting information on virtually all baseball-related processes. Great progress has been made in understanding many physical and physiological influences on performance, and some progress has been made in understanding psychological factors that impact performance (see Chen et al., 2017; Gray, 2010; Ranganathan & Carlton, 2007; Takeuchi & Inomata, 2009). However, far fewer advances have been seen in our understanding of the psychophysiological processes that shape performance.

To address this issue, researchers have begun to examine patterns of neural activity in baseball players, with a focus on assessing hitters' neural activity during pitch perceptions (Chen, Chang, & Huang, 2022; Chen, Chang, Huang, & Yen, 2020; Muraskin, Sherwin, & Sajda, 2013, 2015; Nakamoto & Mori, 2008, 2012; Radlo et al., 2001; Sherwin et al., 2012). These studies explored hitters' anticipatory processes (Chen et al., 2020, 2022), hitters' selection of motor responses (Nakamoto & Mori, 2008, 2012), and hitters' ability to recognize different pitch types (Muraskin et al., 2013; Radlo et al., 2001; Sherwin et al., 2012) using a combination of electroencephalogram (EEG) and functional magnetic resonance imaging methodologies. This research provided insights into the neural networks and timing of neural activation related to pitch classification processes and also showed that expert hitters exert greater inhibitory control—the ability to inhibit unwanted actions—during hitting (Muraskin et al., 2013, 2015; Nakamoto & Mori, 2008, 2012).

Additional research has further explored the link between hitting and inhibitory control and other self-regulatory control processes (Themanson, Bing, Sheese, & Pontifex, 2019; Themanson, Hay, Sieving, & Sheese, 2021). Self-regulatory control refers to the monitoring and control of one's decisions and actions to meet intended goals (Gehring & Knight, 2000) when competing needs or responses are present (Shenhav et al., 2013). Processes that demand control are not automatic; rather, they typically involve effortful monitoring, motivation, regulation, or decision-making processes that are ongoing throughout difficult, erroneous, or novel task execution (Holroyd & McClure, 2015; Holroyd & Yeung, 2012; Shenhav et al., 2013). Accordingly, self-regulatory control reflects a higher order executive function that manages task-relevant cognitive, action, and decision-making processes in real time during task engagement. A number of neural measures of self-regulatory control have been identified and can be assessed using event-related brain potentials (ERPs). ERPs are collected from a person's scalp and provide a measurement of neural activity that is time locked to discrete events (Coles et al., 1990). Furthermore, these brain potentials (ERPs) can continuously measure neural activation throughout a person's engagement with a task and are multifaceted, with different ERP components indexing different cognitive or mental processes (Luck, 2005).

Two ERP components related to self-regulatory control that occur during a hitter's perception of a pitch (stimulus-locked ERPs) have been identified, the N2 and the medial–frontal negativity (MFN; Themanson et al., 2021). The N2 is generated by the anterior cingulate cortex (van Veen & Carter, 2002), a structure that is integral to the implementation of self-regulatory control (Holroyd & Yeung, 2012; Lieberman & Eisenberger, 2015; Shenhav et al., 2013) and has been associated with hierarchical reinforcement learning processes (Botvinick et al., 2009; Holroyd & Yeung, 2012) utilized to select appropriate actions during task engagement and extended sequences of actions. As a result, the N2 provides a measure of response inhibition and conflict-monitoring processes during task execution (Clayson & Larson, 2012; Folstein & Van Petten, 2008; Yeung et al., 2004). Response inhibition refers to the process of stopping a response to execute a different response. This can refer to stopping a response entirely and choosing to not respond—as in a go/no-go paradigm—or it can refer to the process of inhibiting an incorrect response to execute a correct response—as in an Eriksen flanker paradigm (Folstein & Van Petten, 2008).

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This inhibitory process reflects conflict between multiple response options that exist during task execution, and the proper engagement in this self-regulatory process helps to ensure that engaged responses better match intended goals (Clayson & Larson, 2012; Folstein & Van Petten, 2008; Larson et al., 2014; Yeung et al., 2004). In baseball, this process can be seen in swing/no swing decisions for hitters. The hitter needs to inhibit one decisional response (i.e., swing or no swing) for each pitch to engage the correct response for that pitch. This higher order process exists for each pitch independent of motor/response activation to help the hitter ensure that actions, or nonactions, are properly engaged to meet intended goals. Hitters that more effectively engage in this regulatory process should have their performance outcomes match their goals more closely.

Like the N2, the MFN is also generated by the anterior cingulate cortex (West, 2003). The MFN provides a measure of conflict monitoring (Larson et al., 2014; West & Bailey, 2012) and conflict adaptation (West & Alain, 2000), with larger MFN amplitudes associated with greater interference. These findings support the link between the MFN and proactive control that is sustained throughout task engagement rather than reactive control that is initiated as conflict is detected (Braver, 2012; West & Bailey, 2012). Proactive control refers to the anticipatory early selection and maintenance of goal-relevant information to bias attentional and action systems to minimize the effects of interference before they occur and sustain goal-directed processing during task engagement (Braver, 2012). In baseball, this refers to hitters' sustained active maintenance of task goals (e.g., swing at strikes and do not swing at balls) during time intervals between pitches and/or in anticipation of the next pitch throughout the duration of the task to better prepare for the next pitch. Hitters that actively sustain and maintain task goals and bias attentional and action processes toward goal-directed outcomes throughout task engagement should perform more effectively.

These two neural measures of self-regulatory control have been associated with task performance during the completion of a computerized pitch perception task in baseball players (Themanson et al., 2021). Both the N2 and MFN were positively associated with task performance, with larger (more negative) N2 and MFN amplitudes related with more accurate task performance in determining whether pitches were balls or strikes. Following from these findings, it has been proposed that inhibitory control and proactive control may be candidate mechanisms underlying baseball players' enhanced abilities to engage self-regulatory processes during pitch perception and produce better performance during hitting tasks wherein ball/strike and swing/no swing decisions are present (Themanson et al., 2021).

The current study expands on this foundational research to explore the specific relationships between N2 and MFN amplitudes with actual in-game hitting performance for collegiate baseball players. If inhibitory control and proactive control are mechanisms through which baseball players are able to enhance hitting performance, then measures of these two self-regulatory control processes, including the N2 and MFN, should show positive relationships with in-game hitting performance. Accordingly, we hypothesized that larger (more negative) N2 and MFN amplitudes would be associated with better in-game hitting performance in baseball players, suggesting that inhibitory control and proactive control are positively associated with performance outcomes in baseball. We also collected data on other psychological variables that have been associated with performance to better determine the unique relationships N2 and MFN amplitudes have with hitting performance. These findings would extend previous research on the topic (Muraskin et al., 2013, 2015; Nakamoto & Mori, 2008, 2012; Themanson et al., 2021) and provide new evidence and insights into the translational relationship between laboratory-based measures of self-regulatory control processes and performance on the field over time.

Methods

Participants and Psychological Assessment

Nineteen active Division III collegiate baseball players between the ages of 18 and 22 years volunteered to participate in the study (age: $M = 19.8$ years, $SD = 1.4$). Players received no course credit or compensation for their participation. Players ($n = 1$) with excessive noise and artifacts obtained during ERP data collection were discarded from the analyses as were players ($n = 4$) who did not have at least 50 official plate appearances in the college baseball season immediately following the collection of their neural data, resulting in a final sample size of 14 collegiate baseball players. All players reported normal or corrected vision. The study was approved by the institutional review board at the participating institution, and all players signed an informed consent form indicating their willingness to participate and their understanding of the research protocols. Following the completion of the informed consent, players completed a number of measures to assess their anxiety, affect, and personality. State and trait anxiety were assessed using the State-Trait Anxiety Inventory (Spielberger et al., 1983). Positive and negative affect were assessed using the Positive and Negative Affect Schedule (Watson et al., 1988), and five-factor personality was assessed using a 100-item personality inventory developed from the International Personality Item Pool Scale (Goldberg, 1999; Goldberg et al., 2006).

Paradigm

Players were asked to determine whether computerized baseball pitches were balls or strikes. Players sat 1 m in front of a computer monitor and viewed a series of pitches being thrown by a computerized baseball pitcher. The computerized video was recorded using virtual reality software (Big Hit VR Baseball, version 1.0.1, Big Hit Games). Recordings of each pitch video utilized a virtual reality headset to record the pitch from the visual perspective inside the batter's box, and recordings were made from each batter's box to allow players to complete the task from a realistic visual perspective based on their handedness while batting (i.e., right, left, and switch). Players were instructed to sit quietly and remain still, including keeping their heads and eyes still, to minimize head and eye movement artifacts from the neural data. Each pitch video lasted a total of 1,000 ms. Each video started as the release of the pitch was occurring, with the actual pitch occurring over the first 400–500 ms of each video (depending on the pitch type) and continuing for the duration of the 1,000 ms. Players responded within the first 500 ms of each pitch video (i.e., while the pitch was in the air) to reliably replicate the timing of a swing decision and behavior during an actual plate appearance. Responses were recorded on a response pad with players pressing a button with their left thumb indicating that the pitch was a ball or with their right thumb indicating that the pitch was a strike. Visual feedback was given immediately following the conclusion of each pitch video and lasted for 1,000 ms. The feedback indicated whether the player had made a correct or incorrect ball/strike decision (similar to the feedback hitters receive from an umpire). 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). All of the pitch videos and feedback stimuli were presented within a visual display that only subtended a vertical visual angle of 7.44° and a horizontal visual angle of 9.72° to ensure that head and eye movements were not necessary to perform the task. Furthermore, the pitching motion from the release point when each video started continuing through the pitcher's follow-through was identical for each pitch, regardless of pitch type or whether the pitch was a ball or strike, to control for any confounds due to differences in pitcher mechanics. Participants completed four blocks of 50 pitches each for a total of 200 pitch trials. Players saw a random array of six different pitch types (fastball, curve, slider, cutter, sinker, and changeup) within each pitch block. Two blocks of the task utilized a right-handed pitcher, and the other two blocks utilized a left-handed pitcher. The four task blocks were counterbalanced across players, and ball and strike pitches were randomly ordered and equiprobable within each task block. Of the 100 strike pitches, there were 20 fastball strikes and 16 strikes from each of the other pitch types (curve, slider, cutter, sinker, and changeup). Of the 100 ball pitches, there were 20 fastball ball pitches, with five ball pitches at each ball location (high, low, inside, and outside). There were 16 ball pitches for each other pitch type, with four ball pitches at each ball location (high, low, inside, and outside). The virtual pitch speeds ranged from a high speed of 94 mph (fastest fastball speed) to a low speed of 76 mph (slowest curveball speed). The results and theoretical implications from the study were not shared with the players prior to the following baseball season to avoid any potential confounding influences on in-game performance.

Behavioral Assessment

For the assessment of in-game hitting performance in this study, publicly available game statistics were collected from team websites for the players in the study. The statistics that were collected were batting average (BA), on-base percentage (OBP), slugging percentage (SLG), and on-base plus SLG (OPS) for each of the players during the collegiate baseball season that occurred immediately following each player's laboratory assessment.

Neural Assessment

This study used an EEG to measure ongoing neural activity during the pitching paradigm and create ERPs for each pitch during the paradigm. ERPs possess a superior temporal resolution when compared with functional neuroimaging techniques (functional magnetic resonance imaging) and can provide valuable insights into the dynamic neural responses to baseball pitches on a millisecond level, which is not possible with functional magnetic resonance imaging technology (Kappenman & Luck, 2016; Luck, 2005).

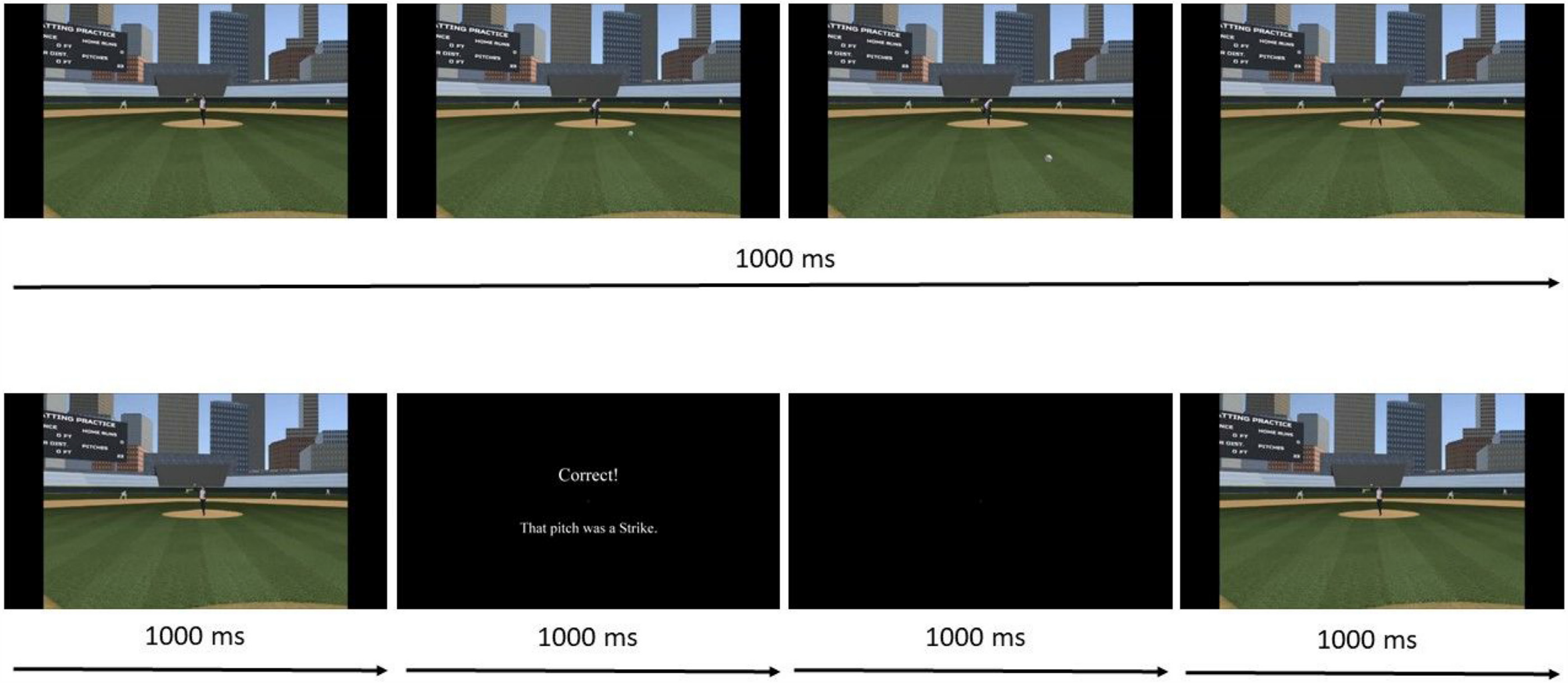
The EEG was recorded from 64 sintered Ag–AgCl electrodes embedded in a Lycra cap arranged in an extended montage based on the international 10–10 system (Chatrain et al., 1985) with a ground electrode (AFz) on the forehead. The sites were referenced online to a midline electrode placed at the midpoint 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 (Neuro Inc.), with a 24-bit analog-to-digital 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). Psychology software (PsychoPy, version 1.84.2) was used for stimulus and feedback presentation and to record participant responses.

Offline processing of the EEG to identify 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 ms to 0 ms prior to the pitch), bandpass 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 from the EEG (Pontifex et al., 2010; Themanson et al., 2019, 2021).

For both the N2 and MFN, the measurement window parameters were determined by creating overall average waveforms across all pitches and players (i.e., collapsed localizers; Luck & Gaspelin, 2017; Themanson et al., 2021). N2 was quantified as the average amplitude between 200 and 330 ms poststimulus in the average waveform of all pitch stimulus events at FCz. MFN was quantified as the average amplitude between 330 and 550 ms poststimulus in the average waveform of all pitch stimulus events at FCz. The data for each participant were outputted into SPSS (version 25.0) for statistical analysis.

Statistical Analysis

Primary analyses were conducted using hierarchical stepwise multiple regression analyses. Prior to hypothesis testing, bivariate Pearson product–moment correlations were calculated between hitting statistics in the season following the study, N2 amplitude, MFN amplitude, and a number of individual difference factors, including personality, anxiety, affect, age, and number of career plate appearances. Correlations including personality, anxiety, and affect were examined due to findings in previous research showing relations between these individual difference variables and either N2, MFN, or task performance (Murray & Janelle, 2003; Sehlmeyer et al., 2010). Furthermore, age and the number of career plate appearances were included in correlational analyses as these variables may be associated with hitting statistics (i.e., the more plate appearances you get and the longer you play in games, the better you are at hitting). Separate analyses were conducted for hitting statistics with each neural component of interest (N2 and MFN). Any individual difference factors significantly correlated with hitting statistics were entered in the first step of the analysis (Miller & Chapman, 2001), and independent factors were added in the subsequent step of the analysis. Goodness of fit of the models was considered in terms of variance explained by the variables in the equation, expressed as R^2. The increase in variance explained by the models was testing for significance after each step to establish whether independent factors (N2 and MFN) accounted for a significant proportion of the variance in the dependent measures. The alpha level was set at $p \leq .05$ for each individual analysis, and all analyses included every participant in the final sample with hitting statistics.



Correct!

That pitch was a Strike.

Figure 1 — At top, visual presentation of pitch stimuli viewed by participants. This figure shows four still frames captured from within a pitch video for right-handed batters facing a right-handed pitcher. The entire duration of each pitch video was 1,000 ms. Images at the bottom show 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.

Results

Table 1 summarizes player values for hitting statistics as well as their neural measures in the task. Figure 2 provides ERP waveforms averaged across all players and pitch stimuli in the task, highlighting the observed N2 and MFN components. Bivariate correlations were calculated between each of these neural measures and available hitting statistics (BA, OBP, SLG, and OPS) for the following season. Due to shortened 2020 and 2021 college baseball seasons, a minimum of 50 plate appearances was required for players to be included in the analyses ($n = 14$). Correlations revealed significant relationships between N2, MFN, and hitting statistics for college players, with larger (more negative) N2 and MFN amplitudes associated with each higher BA, OBP, SLG, and OPS. In addition, bivariate correlations were calculated between the hitting statistics, number of career plate appearances, age, five-factor personality, state and trait anxiety, and negative and positive affect. Correlations revealed that negative affect was correlated with hitting statistics. No other variables were correlated with any of the hitting statistics. Table 2 provides correlation coefficients among hitting statistics, measures of neural activity, and individual difference variables for the players in the study.

Previous research has revealed relationships between the N2 and MFN and performance in this task (Themanson et al., 2021). Accordingly, we examined correlations between the N2, MFN, and response accuracy in the task to confirm previous findings. Analyses revealed similar relationships to previous research with greater (more negative) N2, $r = -.38$, $p = .18$, and MFN amplitudes,

Table 1 Batting Average, On-Base Percentage, Slugging Percentage, OPS, N2 Amplitude, and Medial-Frontal-Negativity Amplitude for Baseball Players in the Baseball Season Immediately Following the Computerized Paradigm

Variable	*M* (*SD*)	Min–max
Batting average	0.294 (0.084)	0.147–0.455
On-base percentage	0.398 (0.082)	0.216–0.510
Slugging percentage	0.379 (0.123)	0.147–0.591
OPS (on-base plus slugging percentage)	0.780 (0.194)	0.363–1.101
N2 amplitude	−6.87 μV (3.66)	−0.86 to −12.96
Medial–frontal negativity	−4.60 μV (3.66)	1.11 to −12.53

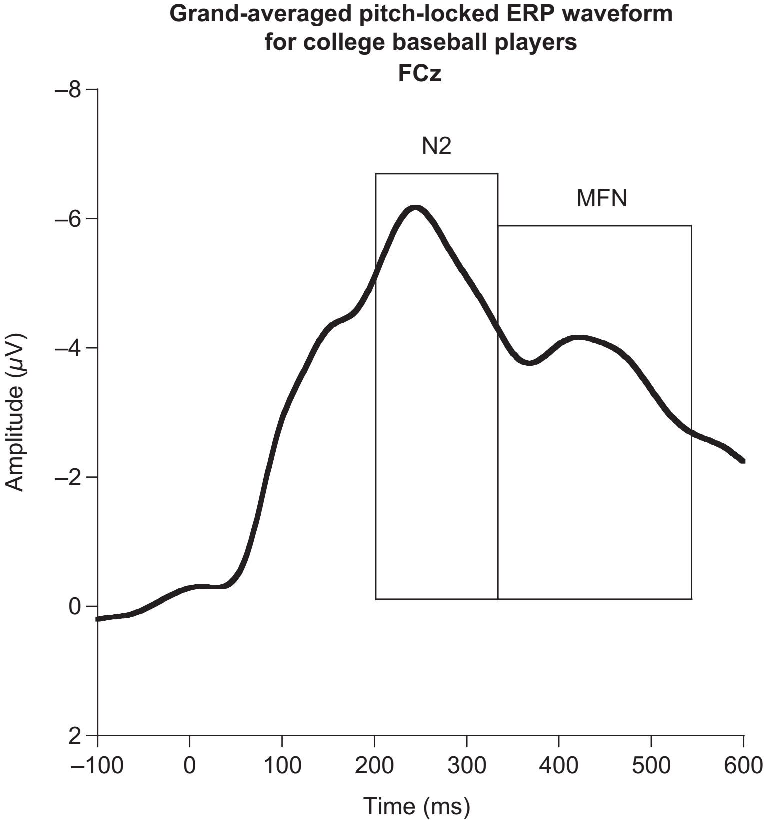


Figure 2 — Grand-averaged pitch-locked waveforms for all pitch stimuli at the FCz electrode site. MFN = medial–frontal negativity; ERP = event-related brain potentials.

$r = -.36$, $p = .21$, associated with greater response accuracy. Although these relationships were not as strong in the current sample compared with those found in previous research, they support the broader finding that self-regulatory neural activity is related with baseball performance. We also assessed relationships between task performance in the current paradigm and hitting performance. The relationships were in the expected direction, with better task performance associated with better hitting performance, but the relationships were not statistically significant, $rs \leq .28$, $ps \geq .35$, suggesting that behavioral performance specifically on the computerized paradigm in this study may not be a useful assessment tool for overall hitting performance.

To more thoroughly examine the relationships found between N2, MFN, and in-game hitting statistics, analyses were conducted using hierarchical stepwise multiple regression to assess the unique relationships between N2 amplitude and MFN amplitude and OPS in the following season. For these analyses, negative affect was entered as a covariate in the first step of each analysis, and N2 amplitude and MFN amplitude, respectively, were entered in the second steps of their analyses. Results presented here detail the regression analyses examining OPS. Similar analyses were conducted for each of the other hitting statistics (BA, OBP, and SLG) for the following baseball season. Regression analyses revealed significant effects for both the N2 and MFN with both BA and SLG, but no significant effects were present with OBP.

The overall regression model including the N2 was significant, $R^2 = .71$, $F(2, 11) = 5.5$, $p = .02$, and revealed a significant effect for N2 in the second step, $\Delta R^2 = .23$, $F(1, 11) = 4.97$, $p = .05$, suggesting a unique association between N2 amplitude and OPS above and beyond the relationship negative affect had with OPS in the following season (see Table 3 left). For the MFN, the overall regression model was significant, $R^2 = .70$, $F(2, 11) = 5.4$, $p = .02$, and revealed a significant effect for MFN in the second step, $\Delta R^2 = .22$, $F(1, 11) = 4.8$, $p = .05$, suggesting a unique association between MFN amplitude and OPS above and beyond the relationship negative affect had with OPS in the following season (see Table 3 right). Figure 3 provides a scatterplot of the relationship between the residuals of N2 and OPS after removing the effect of negative affect from both variables, and Figure 4 provides a scatterplot between the residuals of MFN and OPS after removing the effect of negative affect from both variables.

Table 2 **Correlations Between Hitting Statistics for the Following Baseball Season, N2 Amplitude, MFN Amplitude, and Individual Difference Variables**

Variable	Batting average	On-base percentage	Slugging percentage	OPS
N2	–.69**	–.60*	–.65*	–.67**
MFN	–.67**	–.56*	–.64*	–.65*
Career plate appearances	.19	.24	.40	.35
Age	.32	.43	.32	.40
F-I	–.16	–.05	–.13	–.11
F-II	.06	.03	.05	.03
F-III	–.22	.12	–.20	–.10
F-IV	–.18	.03	–.27	–.20
F-V	–.14	–.02	.14	.08
State anxiety	.27	.24	.22	–.16
Trait anxiety	.23	.07	.11	.08
Positive affect	–.21	–.30	–.22	–.24
Negative affect	–.57*	–.72**	–.37	–.53*

Note. N2 = N2 amplitude; MFN = medial–frontal negativity; F-I = extraversion; F-II = agreeableness; F-III = conscientiousness; F-IV = emotional stability; F-V = intellect; OPS = on-base plus slugging.
*p < .05. **p < .01.

Table 3 **Summary of the Regression Analysis for Variables Predicting OPS for the Following Baseball Season, Including N2 Amplitude (Left) and MFN Amplitude (Right)**

Variable	*B*	SE *B*	CI *B*	β	Variable	*B*	SE *B*	CI *B*	β
Step 1					Step 1				
NA	–0.04	0.02	[–0.08, –0.01]	–0.52*	NA	–0.04	0.02	[–0.08, –0.01]	–0.52*
Step 2					Step 2				
NA	–0.02	0.02	[–0.06, 0.02]	0.59	NA	–0.02	0.02	[–0.06, 0.02]	–0.29
N2	–0.03	0.01	[–0.06, –0.01]	–0.54*	MFN	–0.03	0.01	[–0.06, –0.01]	–0.53*

Note. NA = negative affect; CI = 95% confidence interval; OPS = on-base plus slugging percentage; MFN = medial–frontal negativity.
*p < .05.

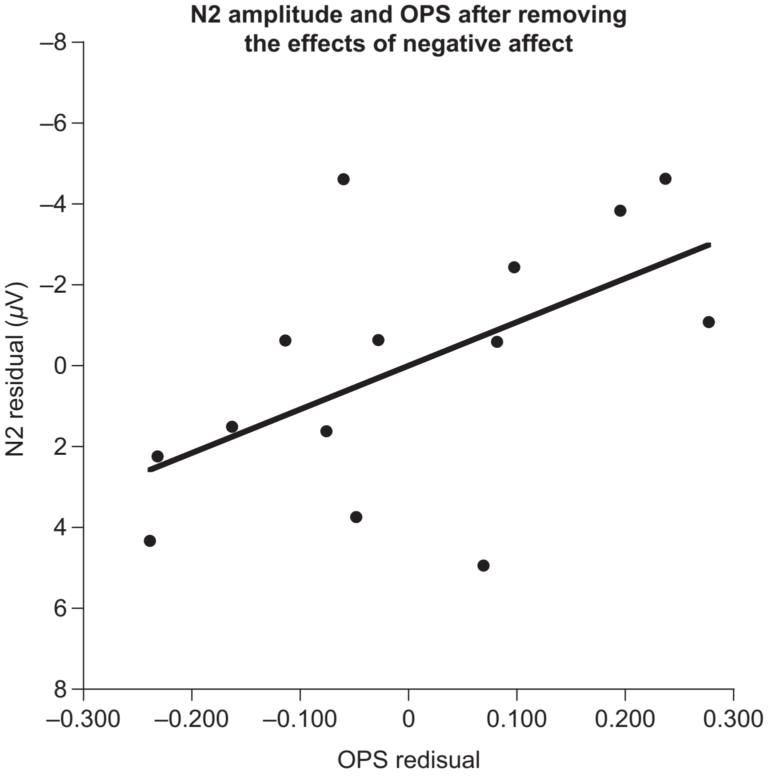


Figure 3 — Scatter plot for the relationship between residuals for N2 amplitude and OPS after controlling for the influence of negative affect. OPS = on-base plus slugging percentage.

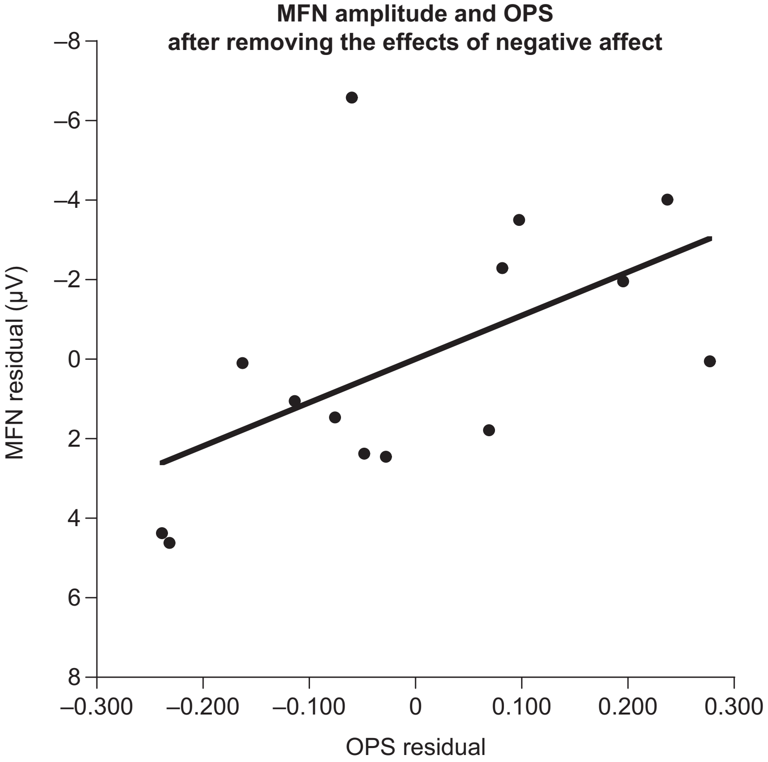


Figure 4 — Scatter plot for the relationship between residuals for MFN amplitude and OPS after controlling for the influence of negative affect. OPS = on-base plus slugging percentage; MFN = medial–frontal negativity.

Discussion

The current study provides evidence for relationships between patterns of neural activity during pitch perception and in-game hitting performance for collegiate baseball players. This study is the first to examine the translational relationship between measures of neural activity obtained during a computerized task and in-game hitting performance. Specifically, we found that greater inhibitory control (measured using N2 amplitude) and greater proactive control (measured using MFN amplitude) were both associated with greater OPS in collegiate baseball players during the baseball season immediately following the study. These relationships were significant and meaningful even after accounting for other individual difference variables known to influence task performance. These relationships between N2, MFN, and OPS were further supported by the relationships that N2 and MFN exhibited with BA and SLG (though these findings were not detailed in this report). These findings speak to the importance of expanding our measurement and information gathering in baseball to include players' cognitive processes and patterns of neural activity. In addition, these findings reveal how self-regulatory control processes measured in a laboratory show beneficial and translational relationships with real-world performance.

Inhibitory Control

We observed that enhanced N2 amplitudes were associated with greater OPS, BA, and SLG in baseball players. Given that the N2 has been related to the inhibitory control of actions (Folstein & Van Petten, 2008) and response conflict processes (Clayson & Larson, 2012), these findings suggest that baseball players executing the task under heightened levels of inhibitory control and conflict adaptation are performing better in games. In baseball, hitters must inhibit one decisional possibility (swing or no swing) in response to each pitch to engage the goal-motivated correct response for that pitch. Inhibitory control is considered vital for the programming and reprogramming of task-relevant action and behavioral flexibility during task execution (Mars et al., 2007; Nakamoto & Mori, 2012). Furthermore, 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).

Proactive Control

In addition to the N2, we also observed significant relationships between the MFN and hitting performance, with greater (more negative) MFN amplitudes associated with greater OPS, BA, and SLG in collegiate baseball players. The MFN has been theorized to reflect proactive control during task engagement (West & Bailey, 2012). Proactive control is described as a preparatory control mechanism, which differs from the reactive control that occurs in response to the momentary detection of conflict. Proactive control aims to prime and sustain task-relevant processing pathways before and throughout task engagement in an effort to adapt performance (Braver, 2012). These performance adaptations and control processes attempt to overcome task-related conflict and continue throughout the performance of a task, from several seconds to several minutes (De Pisapia & Braver, 2006). In baseball, this refers to actively sustaining task goals (e.g., swing at strikes and do not swing at balls) throughout the duration of the task to better prepare for, and perform in response to, the next pitch.

Neural Activity and Performance

The relationships between in-game hitting performance and N2 and MFN amplitudes in the current study support the hypothesis that inhibitory control and proactive control may be mechanisms through which baseball players are better able to perform (Themanson et al., 2021). The present findings further support these claims by providing direct evidence that these components remain meaningful predictors of OPS and other hitting metrics (BA and SLG) after accounting for the effects of other individual difference variables and factors, including career plate appearances, age, anxiety, personality, and affect. Furthermore, these components show relationships with hitting metrics across long periods of time (i.e., months). Accordingly, highlighting inhibitory control and proactive control when working with players may enhance skill acquisition, learning processes, and performance outcomes. These findings are noteworthy in that players' neural activity (measured in a controlled laboratory environment) is showing a translational relationship with in-game hitting performance over time. These relationships persist across these longer time periods because there are stable, trait-like, individual difference factors related with individuals' implementation of inhibitory control, proactive control, and other executive attentional control processes (Braver, 2012), including fluid intelligence (Kane & Engle, 2002) and reward sensitivity (Jimura et al., 2010). These measures of neural activity provide for a more objective analysis of players' ongoing self-regulatory cognitive processes compared with self-report measures. This advances the measurement of cognitive/psychological variables related to in-game performance much like high-speed cameras, motion capture, and force plates have done for physical/physiological variables.

Limitations and Future Directions

One limitation is the small sample size. The limited sample size may have contributed to the notable strength of associations between the neural measures and in-game performance measures observed in the current investigation. Additional investigations utilizing larger samples of player participants may not exhibit the same strength of relationships between neural activity and game performance, although the associations between these measures would persist in meaningful and significant ways across samples and studies. Further evidence for the validity and reliability of the present findings is provided by the consistent pattern of similar relationships observed in previous research examining self-regulatory processes (Arbel & Wu, 2016; Nakamoto & Mori, 2008, 2012; Themanson et al., 2019, 2021). The current study serves to extend and improve upon previous research by examining neural activity to pitch stimuli in relation to actual in-game task performance. Future studies utilizing larger participant samples across levels of play (A, AA, AAA, etc.) are warranted as are study designs that allow for causal inferences and more precise temporal modeling between self-regulatory neural activity and task performance measures.

Conclusions

This research provides the first evidence for the beneficial relationships between patterns of neural activity and in-game hitting performance in baseball. The current study adds to a growing number of studies that show how measures of neural activity can reveal hitters' self-regulatory cognitive processes (Nakamoto & Mori, 2008, 2012;

Themanson et al., 2019, 2021) and extends that work to show how these processes may inform hitters' in-game performance. Neural activity during the pitch reflects response inhibition processes and proactive self-regulatory control processes. These processes are associated with task execution as well as self-regulatory adjustments in motor performance to improve overall outcomes. Furthermore, our findings suggest that players' real-time implementation of self-regulatory control processes, including inhibitory and proactive control obtained through direct measures of their neural activity, is related to their in-game hitting performance and that inhibitory control and proactive control 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. Although trait influences exist, self-regulatory cognitive control is adaptable and trainable (Anguera et al., 2013; Cahn & Polich, 2006; Edwards et al., 2010; Miltner et al., 1988), and a number of factors have been shown to exhibit influences on the magnitude of multiple components of neural activity, including the N2 (Folstein & Van Petten, 2008). Using these neural measures, players, coaches, and organizations can obtain a more objective measure of ongoing self-regulatory processes present during a plate appearance to improve hitting performance in game situations.

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