Psychophysiology, 52 (2015), 1205–1217. Wiley Periodicals, Inc. Printed in the USA.

DOI: 10.1111/psyp.12454

What does cognitive control feel like? Effective and ineffective cognitive control is associated with divergent phenomenology

BLAIR SAUNDERS,[a] MARINA MILYAVSKAYA,[b] AND MICHAEL INZLICHT[a,c]

[a]Department of Psychology, University of Toronto, Toronto, Ontario, Canada
[b]Department of Educational and Counselling Psychology, McGill University, Montreal, Quebec, Canada
[c]Rotman School of Management, University of Toronto, Toronto, Ontario, Canada

Abstract

Cognitive control is accompanied by observable negative affect. But how is this negative affect experienced subjectively, and are these feelings related to variation in cognitive control? To address these questions, 42 participants performed a punished inhibitory control task while periodically reporting their subjective experience. We found that within-subject variation in subjective experience predicted control implementation, but not neural monitoring (i.e., the error-related negativity, ERN). Specifically, anxiety and frustration predicted increased and decreased response caution, respectively, while hopelessness accompanied reduced inhibitory control, and subjective effort coincided with the increased ability to inhibit prepotent responses. Clarifying the nature of these phenomenological results, the effects of frustration, effort, and hopelessness—but not anxiety—were statistically independent from the punishment manipulation. Conversely, while the ERN was increased by punishment, the lack of association between this component and phenomenology suggests that early monitoring signals might precede the development of control-related subjective experience. Our results indicate that the types of feelings experienced during cognitively demanding tasks are related to different aspects of controlled performance, critically suggesting that the relationship between emotion and cognitive control extends beyond the dimension of valence.

Descriptors: Emotion, Cognitive control, Performance monitoring, ERN, Phenomenology, Experience

During effortful situations, such as driving at rush hour, playing a musical instrument, or competing in sports, we often attempt to remain calm, believing that retaining composure facilitates focus on the task at hand. Emotional experiences, however, can and do arise during effortful performance. We might feel anxiety during a musical recital, frustration when we miss our highway exit, or hopelessness when competing against a stronger opponent in sports. But how do these apparently unsolicited feelings relate to performance? Do certain experiences coincide with successful goal-directed actions, while other feelings co-occur with less goal-conducive behaviors? Here, we investigated these questions, asking what feelings accompany effective and ineffective cognitive control.

Negative Affect and Cognitive Control

Cognitive control comprises multiple processes (e.g., goal setting, monitoring, inhibition) that facilitate goal attainment, particularly in challenging circumstances (Banich, 2009; Braver, 2012; Miyake et al., 2000). Several theories have aimed to account for variation in cognitive control, with prevalent models emphasizing computational mechanisms, such as conflict monitoring (Botvinick, Braver, Barch, Carter, & Cohen, 2001) or outcome evaluation (Holroyd & Coles, 2002). In parallel to these cognitive neuroscience accounts, affective science has revealed that goal conflicts (e.g., response conflict, errors) are emotive, triggering negative evaluations (Aarts, De Houwer, & Pourtois, 2013; Dreisbach & Fischer, 2012) and widespread peripheral nervous system activation (e.g., Critchley, Tang, Glaser, Butterworth, & Dolan, 2005; Hajcak, McDonald, & Simons, 2003; Lindström, Mattsson-Mårn, Golkar, & Olsson, 2013). Additionally, the neural substrates of control and emotion overlap substantially, particularly in medial prefrontal structures such as the anterior cingulate cortex (ACC; Koban & Pourtois, 2014; Shackman et al., 2011). Consolidating this evidence, it has recently been suggested that control might resemble an adaptive emotional process, where the negative experience of conflict motivates the instantiation of control (Inzlicht, Bartholow, & Hirsh, 2015).

Besides valence judgments, peripheral arousal, and characteristic neural activations, emotional episodes are also associated with a range of subjective feelings, such as anxiety, anger, or happiness (Barrett, Mesquita, Ochsner, & Gross, 2007). Consequently, if cognitive control is closely aligned with emotional processing (cf. Inzlicht et al., 2015), the obvious question arises: What does cognitive control feel like?

We would like to thank Elizabeth Page-Gould, Nathaniel Elkins-Brown, Vincent Pillaud, Zoë Francis, and Nicholas Hobson for valuable discussions throughout the development of this work. This research was made possible by grants from the Ontario Ministry of Research and Innovation and from Canada's Natural Sciences and Engineering Research Council to Michael Inzlicht.

Address correspondence to: Blair Saunders, Department of Psychology, University of Toronto, 1265 Military Trail, Toronto, Ontario M1C 1A4, Canada. E-mail: blairsaunders01@gmail.com

The Phenomenology of Cognitive Control

Phenomenology is principally concerned with the study of subjective experience (Husserl, 1913/1983), and such investigations have revealed a remarkable heterogeneity in emotion (Barrett, 2013). Regarding goal-directed behavior, emotions might be considered either "helpful" or "harmful" depending on a number of factors, including duration, intensity, and the appropriateness of the emotion for the current situation (Gross & Jazaieri, 2014). Interestingly, while considerable evidence suggests that control is aversive, few investigations have asked what this negative affect actually feels like.

In one study, participants experienced increased anger when they made mistakes in a social context (Koban, Corradi-Dell'Acqua, & Vuilleumier, 2013); however, this data was not used to predict neural monitoring or cognitive control. In another phenomenological investigation, elevated anxiety, frustration, and unpleasantness arose during blocks of an inhibitory control task, relative to blocks that did not tax inhibitory processes (Spunt, Lieberman, Cohen, & Eisenberger, 2012). Furthermore, intraindividual variation in frustration uniquely predicted fMRI activation in the same portion of the ACC that was sensitive to errors, providing preliminary evidence that neural monitoring "feels like frustration" (pp. 1762).

The Current Study

We expanded on these previous studies by investigating the subjective correlates of neurophysiological performance monitoring and cognitive control. At the neural level, we investigated an electrophysiological correlate of performance monitoring: The error-related negativity (ERN; Falkenstein, Hohnsbein, Hoorman, & Blanke, 1991; Gehring, Goss, Coles, Meyer, & Donchin, 1993). The ERN is a negative ERP that peaks at frontocentral electrodes within 100 ms of errors. While this component has been primarily accounted for by computational models of control (Holroyd & Coles, 2002; Yeung, Botvinick, & Cohen, 2004), a number of recent studies have also suggested that the ERN reflects the negative valence of errors (e.g., Aarts et al., 2013; Inzlicht & Al-Khindi, 2012; Wiswede, Münte, Krämer, & Rüsseler, 2009).

Extending this work, we tested if the ERN has a specific phenomenology. Given its putative generator in the ACC (Dehaene, Posner, & Tucker, 1994), it may be hypothesized that the ERN will track subjective frustration (cf. Spunt et al., 2012). However, several factors suggest that an investigation of the ERN may not mirror this earlier result. First, contrasting the fMRI signal, ERPs instantaneously measure bioelectric activity that arises from the summed activation of neuronal assemblies. Indeed, as the ERN unfolds rapidly after mistakes, potentially preceding error awareness (Nieuwenhuis, Ridderinkhof, Blom, Band, & Koch, 2001), it is unclear if this early signal will be related to subjective experience. Second, increased ERN amplitudes are consistently associated with anxious psychopathology and threat sensitivity (e.g., Cavanagh & Shackman, 2014; Weinberg, Riesel, & Hajcak, 2012), proposing that the ERN may increase with subjective anxiety, rather than frustration. Anhedonia and psychomotor retardation, conversely, are associated with reduced ERNs (Ruchsow et al., 2004; Schrijvers et al., 2008), suggesting that related experiences—such as hopelessness—might accompany diminished monitoring.

In addition to the ERN, we investigated the phenomenology of inhibitory control. Recent work indicates that performance on canonical tests of cognitive control (e.g., Stroop and Simon tasks) improves when contexts promote avoidance motivation (e.g., Hengstler, Holland, van Steenbergen, & van Knippenberg, 2014; Shouppe, De Houwer, Ridderinkhof, & Notebaert, 2012). Thus, threat-related feelings, such as subjective anxiety (cf. Gray & McNaughton, 2000), might accompany effective control. It is unlikely to be true, however, that negative emotions are universally associated with increased control. Negative feelings of frustration or anger might underlie uncontrolled, impulsive behaviors, such as interpersonal aggression (Berkowitz, 1989; Bushman, De Wall, Pond, & Hanus, 2014), while hopelessness, on the other hand, is associated with the perceived inability to implement goal-directed actions (Hadley & MacLeod, 2010). Consequently, it might be hypothesized that certain negative experiences (e.g., frustration, hopelessness) will accompany ineffective control.

Thus, negative emotions appear to have a complex relationship with control. As evidence for this heterogeneity has arisen from multiple subdisciplines of psychology, each using relatively idiosyncratic metrics of control (e.g., laboratory protocols, self-report) and emotion (e.g., dispositional affect, mood inductions), a key motivation for the current study was to investigate the relationship(s) between emotion and control within a single inhibitory control paradigm.

Method

Participants

Forty-nine undergraduate students at the University of Toronto Scarborough participated in return for course credit. Seven participants were excluded from all analyses due to either technical problems during the presentation of auditory stimulation (four participants), too few usable ERP trials (< five) to conduct reliable ERN analyses (one participant) (cf. Olvet & Hajcak, 2009), or not correctly following experimental instructions (two participants). Consequently, the final sample comprised 42 participants ($M_{age} = 18.7$, $SD = 1.2$; 33 females). Participants were informed that the purpose of the study was to investigate the relationship between performance and various physiological and psychological states. At study onset, we determined to run the study until the end of the semester, or until we had collected usable data from > 40 participants. We conducted no interim hypothesis testing prior to the conclusion of data collection.

Procedure

Participants performed a speeded inhibitory control task combined with a variable punishment schedule that was contingent on performance accuracy. The primary motivation for this punishment manipulation was to create sufficient variation in affect during task performance to investigate the affective phenomenology of cognitive control. A secondary benefit of this manipulation was the ability to assess the impact of punishment by a primary reinforcer (aversive acoustic stimulation) on the behavioral and neurophysiological correlates of control. As such, the reinforcement schedule employed in the current study (detailed below) closely followed a recent investigation that reported significant effects of acoustic punishment (vs. nonpunishment) on both the amplitude of the ERN and performance on an arrow flanker task (Riesel, Weinberg, Endrass, Kathmann, & Hajcak, 2012).

Participants were seated in a dimly lit room with a viewing distance of approximately 80 cm to the screen. The inhibitory control paradigm consisted of a two-alternative, forced choice task, where the target letter M served as the frequent (.8 probability of occurrence) and target letter W as the infrequent (.2 probability of occurrence) stimuli. Manual responses were recorded using a millisecond accurate DirectIN keyboard (Empirisoft, New York, NY), with key assignment in the standard QWERTY format. Participants were instructed to make a right finger press on the/key if they saw an M target and a left finger press on the Z key if they saw a W target. This asymmetrical ratio of target stimuli was employed to ensure a prepotent response tendency in favor of the frequent stimuli. Thus, one benefit of this two-alternative, forced choice task over more commonly used go/no-go protocols is that a reaction time (RT) measure can be obtained from the manual response to the infrequent stimuli (Lindström et al., 2013). Hereafter, the frequent and infrequent stimuli will be referred to as low-conflict and high-conflict trials, respectively (see Jones, Cho, Nystrom, Cohen, & Braver, 2002).

Each trial started with a blank screen for 200 ms, followed by the brief (200 ms) presentation of a target letter in white font on a black background. The screen then remained blank until response commission (max: 1,000 ms) followed by a white fixation cross that was presented for 400 ms before the start of the next trial. However, if the participant made an error, the screen remained blank for an additional 1,000 ms after the response, before the 1,000-ms presentation of a high-pitched pure tone (3500 Hz). The auditory stimuli were presented using Logitech z523 desktop speakers (Logitech, Fremont, CA) with two desk-level satellite speakers and one floor-level subwoofer (total power: 40W RMS). For punished trials, the tone was played at 100 dB (cf. Riesel et al., 2012), while in the unpunished condition the volume of this tone was reduced by 60% to produce a faint but clearly audible beep. Thus, trial timings were identical between punishment levels, while the aversiveness of the performance-contingent acoustic feedback was manipulated between conditions (see Figure 1).

Participants first completed 20 practice trials without auditory stimulation, before moving on to 840 experimental trials. The experimental trials were further divided into 12 blocks of 70 trials, separated by self-report questions (detailed below) and a self-paced rest period. The punishment schedule was manipulated in a blockwise manner: All participants completed six punished and six unpunished blocks. Furthermore, punishment level alternated in groups of three blocks (e.g., punished [Blocks 1–3]; unpunished [Blocks 4–6]; punished [Blocks 7–9]; unpunished [Blocks 10–12]). The order of punishment-level was counterbalanced across participants, and participants were made aware of the type of auditory stimulation that would be presented before starting each block type: "During this block you will sometimes be presented with LOUD [QUIET] sounds."

Participants reported their subjective experience at the end of each block, resulting in 12 self-report scores for five phenomenological measures. Each question asked participants to reflect over and report their feelings during the previous block of trials. Participants were first instructed to "please answer the following questions about your feelings during the block of trials you just did, using numbers 1–7" (1 = *not at all*; 7 = *extremely*). Three specific questions asked participants to report their affective experience: Anxiety ("How ANXIOUS were you?"), frustration ("How FRUSTRATED were you?"), and hopelessness ("How HOPELESS did you feel?"), while two further questions probed other aspects of phenomenological experience during performance: boredom ("How BORED were you?") and effort ("How HARD did you try?"). The serial order of question presentation was randomized within participants and between blocks.

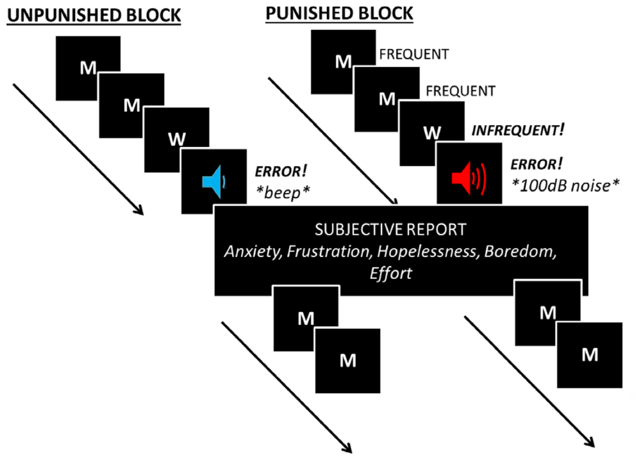

Figure 1. Schematic depiction of the experimental protocol demonstrating a hypothetical error trial on both the unpunished (left) and punished (right) block types.

EEG Preprocessing and ERP Analyses

Continuous EEG activity was recorded from 13 Ag/AgCl sintered electrodes embedded in a stretch Lycra cap. The scalp-electrode montage consisted of midline and frontolateral electrode sites (Fz, F3, F4, F7, F8, FCz, Cz, CPz, and Pz), referenced to the average signal at bilateral earlobes. Vertical electrooculography (VEOG) was monitored using a supra- to suborbital bipolar montage surrounding the right eye. During recording, impedances were monitored (< 5 KΩ), and the EEG signal was digitized at 512 Hz using ASA acquisition hardware (Advanced Neuro Technology, Enschede, The Netherlands). Offline, the data were band-pass filtered (high-pass: 0.1 Hz; low-pass: 20 Hz) and corrected for eyeblinks using regression-based procedures (cf. Gratton, Coles, & Donchin, 1983). Semiautomatic procedures were employed to detect and reject EEG artifacts using BrainVision Analyzer, v.2.0 (Brain Products, GmbH, Gilching, Germany). The criteria applied were a voltage step of more than 25 μV between sample points, a voltage difference of 150 μV within 200-ms intervals, voltages above 85 μV and below −85 μV, and a maximum voltage difference of less than 0.05 μV within 100-ms intervals. These intervals were rejected on an individual channel basis to maximize data retention.

Peak-to-peak measures were used to gain a baseline independent operationalization of the ERPs. The ERN and correct-related negativity (CRN) were defined as the negative maxima 0 to 120 ms after erroneous and correct responses (respectively), relative to the most positive potential proceeding the response (−100 to 0 ms).

Data Reduction

In order to assess the effects of self-reported phenomenology on performance monitoring and cognitive control, the experiment was partitioned into four subsections, each comprising three consecutive blocks of shared punishment valence (i.e., mean [1st three punished blocks], mean [1st three unpunished blocks], and so forth). The rationale for this methodology was to ensure that a sufficient number of errors contributed to each experimental subsection to produce reliable ERNs (Olvet & Hajcak, 2009) while also obtaining variable intraindividual measures of experience during performance. Thus, behavioral measures of inhibitory control (RT and accuracy), subjective self-report measures, and ERPs (ERN, CRN, and ΔERN) were calculated for each participant per experimental quadrant (1st punished, 1st unpunished, 2nd punished, 2nd unpunished). In addition to this traditional ERN analysis, we also conducted an analysis on the difference ERPs (ERN minus CRN), producing what is often referred to as delta ERN (ΔERN). Finally, if participants made < 5 errors in a given quadrant, they were coded as missing data for the error-related ERPs (ERN and ΔERN). This exclusion criterion resulted in approximately 17% missing data for the ERN cells, with participants contributing on average 11.9 errors to each ERN or ΔERN (subsection means ranged from 9.7 to 14.8 errors). Importantly, we used multilevel models for all analyses, which possess a better ability to handle missing data than standard repeated measures analyses (Raudenbush & Bryk, 2002).

Finally, we were interested in assessing the effects of fluctuating affective experiences that arise during performance on the neurophysiological and behavioral correlates of control. Crucially, this hypothesis requires a metric of intraindividual variation in phenomenology. To this end, we computed a participant-centered score for each self-report measure by subtracting the average score for each quadrant from each individual's mean self-report ratings across the entire experiment (e.g., person-centered anxiety = mean anxiety [Blocks 1–3] minus mean anxiety [all blocks]).This procedure allowed us to assess the association between control and within-participant, state-level phenomenology, while diminishing the effects of between-participant, trait-level subjective experience.

Statistical Analyses

All analyses were conducted by multilevel modeling (MLM) using the MIXED function in SPSS (v. 22.0). We first ran a manipulations check to test if our punishment manipulation caused changes in self-reported phenomenology. Each self-report item (anxiety, boredom, effort, frustration, and hopelessness) was analyzed as a function of punishment level (effect coded: unpunished = −1, punished = 1). Therefore, these MLMs had a two-level structure, accounting for experimental quadrant (1 = 1st quiet, 2 = 2nd quiet, 3 = 1st loud, 4 = 2nd loud) nested within participant. Unstructured variance was used to estimate a random intercept for each participant.

For the behavioral data (mean RTs and choice error rates), MLMs comprised the effects of conflict level (−1 = low conflict, 1 = high conflict) and punishment (−1 = unpunished, 1 = punished), as well as the person-centered (quadrant-specific) scores for each of the five self-report variables. Thus, the behavioral analyses now had a three-level structure due to the inclusion of conflict level (i.e., conflict level within quadrant within participant). Initial models included the main effects of conflict level and each of the person-centered self-report ratings. We also included all two-way interactions between conflict level and each self-report measure to test the association between phenomenology and inhibitory control. Initially, we did not include punishment in this model to assess the influence of experience on control without accounting for the effects of punishment. Subsequently, we entered the factor of punishment—modeling the main effect of punishment and the Punishment × Conflict Level interaction—to test the statistical independence of any observed effects from the influence of the externally provided punishment schedule. Conflict level was entered as a repeated measure within each quadrant, with the slope and intercept of conflict level specified as random at the participant level using unstructured variance.

Initial ERP analysis used a three-level model that was identical to the behavioral data, with the exception that the effect of conflict level was replaced by trial type (i.e., trial type within quadrant within participant). This trial type variable accounted for the correct-related (i.e., CRN) and error-related (i.e., ERN) ERPs, using effect coding (−1 = CRN, 1 = ERN). Next, as the ΔERN reflects the difference between error-related and correct-related ERPs, the trial-type factor was removed to create a two-level MLM (i.e., quadrant within participant).

Finally, the principle rationale for splitting the experiment into quadrants was to facilitate investigating the phenomenology of the ERN. However, while ERNs cannot be operationalized reliably at the resolution of the block (see Olvet & Hajcak, 2009), we are able measure control performance (mean RTs, choice error rates) and self-reported experience on a per block basis. Thus, to extend the behavioral analyses, we conducted further MLMs entering each participant's behavioral and experiential data at the resolution of the block (i.e., 12 repeated measures), rather than the aggregate of three blocks as used in the quadrant-level analysis. This method allows us to predict behavior from fluctuating online experiences at the lowest level of temporal resolution available in the current dataset, potentially detecting effects that arise from more phasic shifts in affect that were not detected at the quadrant resolution. In this section, person-centered emotions were calculated by subtracting the block-specific phenomenology from the mean score for that measure across the entire experiment. The MLMs used for this analysis had an identical three-level structure to the prior behavioral analysis, with the exception that the block variable (12 repeated measures) replaced the quadrant variable.

For all analyses, effects were determined to be statistically robust if the 95% confidence intervals for the given main effect or interaction did not span zero (Cumming, 2013). Semipartial R ^{2} (R^2_β) is reported as an effect size for each model effect (Edwards, Muller, Wolfinger, Qaqish, & Schabenberger, 2008).

Results

Manipulations Check

Anxiety ratings were higher during the punished than unpunished blocks ($b = -1.06$, $SE = 0.14$, 95% CIs [−1.34, −0.79]), $R^2_\beta = .32$. Similar increases were also found for self-reported frustration ($b = -0.32$, $SE = 0.15$, 95% CI [−0.63, −0.02]), $R^2_\beta = .03$; hopelessness ($b = -0.27$, $SE = 0.12$, 95% CIs [−0.52, −0.03]), $R^2_\beta = .04$; and effort ($b = -0.47$, $SE = 0.12$, 95% CIs [−0.70, −0.24]), $R^2_\beta = .12$. In contrast, participants reported less boredom in the punished compared to the unpunished condition, ($b = 0.38$, $SE = 0.14$, 95% CIs [0.10, 0.65]), $R^2_\beta = .06$. Thus, our punishment manipulation successfully induced variation across all self-report dimensions, see Figure 2. However, it is also clear that punishment had the largest influence on self-reported anxiety—note that the lower bound of the 95% CIs for anxiety is higher than the upper bound of the 95% CIs for all other self-report items.

Behavioral Data: Quadrant Level

Next, we investigated our primary topic of interest, the relationship between self-reported experience and the behavioral implementation of cognitive control. For the sake of brevity, we only report statistically significant effects in this section, with all model effects (parameter estimates, standard errors, and confidence intervals) summarized in Table 1.

Choice error rates. Indicating that our conflict manipulation was successful, participants made more mistakes on high-conflict ($M =$

Figure 2. Bar chart depicting mean experience ratings as a function of punishment condition. Error bars depict within-subject confidence intervals.

23.6%, *SE* = 2.4) than low-conflict trials (*M* = 0.8%, *SE* = 0.6), ($b = -22.76$, *SE* = 1.93, 95% CIs [−26.66, −18.85]), $R^2_\beta = .77$. Error rates also increased with increasing frustration ($b = 3.89$, *SE* = 0.99, 95% CIs [1.93, 5.85]), $R^2_\beta = .12$, while participants became more accurate as they became more anxious ($b = -4.01$, *SE* = 1.03, 95% CIs [−6.04, −1.97]), $R^2_\beta = .11$. Interestingly, we also observed significant interactions between conflict level and frustration ($b = -3.77$, *SE* = 1.02, 95% CIs [−5.78, −1.75]), $R^2_\beta = .10$, and between conflict level and anxiety ($b = 4.02$, *SE* = 1.06, 95% CIs [1.93, 6.11]), $R^2_\beta = .11$. Follow-up simple effects tests revealed that increasing frustration levels were associated with heightened error rates on high-conflict trials ($b = 3.89$, *SE* = 0.99, 95% CIs [1.93, 5.86]), $R^2_\beta = .11$, but not low-conflict trials ($b = 0.13$, *SE* = 0.10, 95% CIs [−0.07, 0.32]), $R^2_\beta = .01$, see Figure 3A. In contrast, identical tests revealed that high-conflict error rates reduced as a function of increasing anxiety ($b = -4.01$, *SE* = 1.03, 95% CIs [−6.04, −1.97]), $R^2_\beta = .11$, whereas anxiety was not associated with low-conflict error rates ($b = 0.01$, *SE* = 0.10, 95% CIs [−0.19, −0.22]), $R^2_\beta < .01$, see Figure 3A.

Thus, this initial model suggests that intraindividual variation in frustration and anxiety have divergent relationships with high-conflict error rates. Increasing frustration predicted increased high-conflict error rates, whereas lower levels of anxiety were associated with reduced high-conflict error rates.

We then entered the punishment factor into this model, calculating the additional main effect of punishment and the Punishment × Trial Type interaction. In this model, frustration predicted increased error rates ($b = 3.86$, *SE* = 0.86, 95% CIs [2.25, 5.57]), $R^2_\beta = .16$, and this main effect interacted with conflict level, ($b = -3.73$, *SE* = 0.90, 95% CIs [−5.52, −1.94]), $R^2_\beta = .12$. Conversely, no other effects involving self-reported emotion—including the previously significant effects of anxiety—were present when punishment was included in the model, see Figure 3B. Importantly, we also observed that error rates decreased in the punished compared to the unpunished condition ($b = -4.81$, *SE* = 0.78, 95% CIs [−6.36, −3.26]), $R^2_\beta = .26$, and that this main effect interacted with conflict level, ($b = 4.74$, *SE* = 0.82, 95% CIs [3.12, 6.35]), $R^2_\beta = .22$, see Figure 3C. Follow-up simple effects tests revealed that the punishment condition was associated with significantly reduced error rates for high-conflict trials relative to the unpunished condition ($b = -4.81$, *SE* = 0.78, 95% CIs [−6.36, −3.26]), $R^2_\beta = .24$. Conversely, error rates did not differ between punishment conditions for low-conflict trials ($b = -0.07$, *SE* = 0.90, 95% CIs [−0.25, 0.10]), $R^2_\beta < .01$.

Consequently, while the negative association between accuracy and subjective frustration was statistically independent from the punishment manipulation, the previously significant association between anxiety and performance appeared to be statistically dependent upon the punishment schedule. Indeed, punishment—akin to anxiety in the prior model—was associated with a significant reduction in error rates to high-conflict trials.

Mean RTs. Participants responded more slowly on high-conflict (*M* = 441 ms, *SE* = 6) than low-conflict (*M* = 335 ms, *SE* = 6) trials ($b = -106.08$, *SE* = 4.86, 95% CIs [−115.89, −96.27]), $R^2_\beta = .92$, thus confirming that the conflict manipulation was successful. Mean RTs also generally increased with increasing self-reported boredom ($b = 8.11$, *SE* = 2.79, 95% CIs [2.58, 13.64]), $R^2_\beta = .06$. The main effect of conflict level further interacted with frustration ($b = -13.19$, *SE* = 3.29, 95% CIs [−19.70, −6.70]), $R^2_\beta = .12$, and anxiety ($b = 8.06$, *SE* = 3.41, 95% CIs [1.31, 14.80]), $R^2_\beta = .04$. Follow-up simple effects tests revealed that the interaction between conflict level and frustration was due to RT speeding with increasing frustration for the frequent, low-conflict trials ($b = -11.05$, *SE* = 2.23, 95% CIs [−15.47, −6.63]), $R^2_\beta = .11$, but not for the infrequent, high-conflict trials, ($b = 2.13$, *SE* = 2.56, 95% CIs [−2.93, 7.19]), $R^2_\beta < .01$. In contrast, RTs became slower on low-conflict trials with increasing anxiety ($b = 9.05$, *SE* = 2.31, 95% CIs [4.48, 13.63]), $R^2_\beta = .17$, while anxiety levels were not associated with high-conflict RTs ($b = 1.00$ *SE* = 2.65, 95% CIs [−4.24, 6.24]), $R^2_\beta < .01$. Thus, while frustration was associated with speeding of the prepotent response (i.e., low-conflict RT), anxiety co-occurred with slowing on the same trials.

We then entered the punishment effects into this model as a covariate, modeling both the main effect of punishment and the Punishment × Trial Type interaction. In this extended model, the main effect of boredom ($b = 8.54$, *SE* = 2.83, 95% CIs [2.93, 14.14]), $R^2_\beta = .09$, and the interaction between frustration and trial type were maintained ($b = -13.14$, *SE* = 3.25, 95% CIs [−19.57, −6.71]), $R^2_\beta = .12$.[1] Finally, punishment also interacted with conflict level ($b = 5.87$, *SE* = 2.93, 95% CIs [0.06, 11.67]), $R^2_\beta = .03$; this was due to punishment driving increased RT slowing for the low-conflict trials ($b = 8.07$, *SE* = 1.88, 95% CIs [4.34, 11.80]), $R^2_\beta = .13$, but not the high-conflict trials ($b = 2.20$, *SE* = 2.31, 95% CIs [−2.37, 6.77]), $R^2_\beta < .01$. In contrast, no effects of anxiety—main effect or interaction—were significant in this model, see Table 1.

Considered together, the behavioral results (both RTs and error rates) suggest that frustration and anxiety had divergent associations with response caution. Frustration predicted more careless actions (faster and less accurate), while anxiety predicted increasingly cautious (slower and more accurate) responses. Importantly, all relationships between anxiety and performance were no longer significant when analyses controlled for punishment, suggesting that these changes in response caution were mainly attributable to the punishment manipulation, rather than subjective anxiety per se.

ERP Data

We now turn our attention to the analyses of error-related ERPs (CRN, ERN, ΔERN), investigating the potential phenomenological correlates of early neurophysiological reactivity to errors. As with prior analyses, we do not report the statistics for nonsignificant

1. Follow-up simple effects test revealed an identical pattern of results that occurred before punishment was entered into the model.

Table 1. *Summary of MLM Results for the Quadrant-Level Analyses (Significant Results in Bold)*

	Reaction time				Choice error rates			
Model without punishment	*b*	*SE*	95% CIs	R^2_β	*b*	*SE*	95% CIs	R^2_β
Conflict level	**−106.08**	**4.86**	**[−115.89, −96.27]**	**.92**	**−22.76**	**1.93**	**[−26.66, −18.85]**	**.77**
Anxiety	1.00	2.65	[−4.24, 6.24]	.06	**−4.01**	**1.03**	**[−6.04, −1.97]**	**.11**
Anxiety*Conflict level	**8.06**	**3.41**	**[1.31, 14.80]**	**.04**	**4.02**	**1.06**	**[1.93, 6.11]**	**.11**
Boredom	**8.11**	**2.79**	**[2.58, 13.64]**	**.06**	0.92	1.08	[−1.22, 3.07]	< .01
Boredom*Conflict level	−5.18	3.59	[−12.29, 1.94]	.02	−1.00	1.11	[−3.20,1.21]	< .01
Effort	0.94	3.54	[−6.07, 7.94]	< .01	−1.63	1.37	[−4.35, 1.09]	.02
Effort*Conflict level	0.71	4.56	[−8.31, 9.74]	< .01	1.38	1.41	[−1.42, 4.17]	< .01
Frustration	2.13	2.56	[−2.92, 7.19]	.05	**3.89**	**0.99**	**[1.93, 5.85]**	**.12**
Frustration*Conflict level	**−13.19**	**3.29**	**[−19.70, −6.70]**	**.12**	**−3.77**	**1.02**	**[−5.78, −1.75]**	**.10**
Hopelessness	−2.25	3.31	[−8.81, 4.30]	< .01	1.03	1.28	[−1.51, 3.57]	< .01
Hopelessness*Conflict level	−0.09	4.26	[−8.52, 8.34]	< .01	−1.15	1.32	[−3.76, 1.46]	< .01
Model including punishment	*b*	*SE*	95% CIs	R^2_β	*b*	*SE*	95% CIs	R^2_β
Conflict level	**−106.08**	**4.86**	**[−115.89, 96.27]**	**.92**	**−22.80**	**1.93**	**[−26.66, −18.85]**	**.77**
Anxiety	−0.35	3.00	[−6.29, 5.59]	< .01	−1.06	1.02	[−3.08, 0.96]	< .01
Anxiety*Conflict level	4.46	3.81	[−3.09, 12.01]	.01	1.12	1.06	[−0.98, 3.22]	< .01
Boredom	**8.54**	**2.83**	**[2.93, 14.14]**	**.09**	−0.01	0.96	[−1.91,1.89]	< .01
Boredom*Conflict level	−4.04	3.60	[−11.16, 3.08]	.01	−0.08	1.00	[−2.06, 1.90]	.01
Effort	0.95	3.54	[−6.07, 7.96]	< .01	−1.65	1.20	[−4.03, 0.73]	.02
Effort*Conflict level	0.74	4.50	[−8.17, 9.66]	< .01	1.40	1.25	[−1.08, 3.88]	.01
Frustration	2.15	2.57	[−2.91, 7.21]	.05	**3.86**	**0.86**	**[2.25, 5.57]**	**.16**
Frustration*Conflict level	**−13.14**	**3.25**	**[−19.58, −6.71]**	**.12**	**−3.73**	**0.90**	**[−5.52, −1.94]**	**.12**
Hopelessness	−2.06	3.32	[−8.63, 4.50]	< .01	0.61	1.13	[−1.61, 2.84]	< .01
Hopelessness*Conflict level	0.42	4.21	[−7.92, 8.77]	< .01	−0.74	1.73	[−3.06, 1.59]	< .01
Punishment	**2.20**	**2.31**	**[−2.37, 6.77]**	**.09**	**−4.81**	**0.78**	**[−6.36, −3.26]**	**.26**
Punishment*Conflict level	**5.87**	**2.93**	**[0.06, 11.67]**	**.03**	**4.74**	**0.82**	**[3.12, 6.35]**	**.22**

effects in this section. Please refer to Table 2 for full model statistics.

ERN. Indicating that we observed a reliable ERN, ERP amplitudes were more negative following erroneous ($M = -18.87$ µV; $SE = 1.10$) than accurate ($M = -2.45$ µV; $SE = 0.40$) performance ($b = 16.00$, $SE = 1.01$, 95% CIs [13.97, 18.04]), $R^2_\beta = .86$, see Figure 4. In contrast to the behavioral results, however, self-reported phenomenology did not predict any ERPs results; see Table 2.[2]

In a second model, we tested the effect of punishment on performance monitoring. We removed the subjective-report information from this model as these ratings were not associated with the neurophysiological results in the prior analyses. Interestingly, this model revealed a significant main effect of punishment ($b = 2.94$, $SE = 1.10$, 95% CIs [0.77, 5.12]), $R^2_\beta = .10$. This effect was due to ERP amplitudes being generally more negative for punished ($M = -11.50$ µV; $SE = 0.66$) than unpunished blocks ($M = -9.84$ µV; $SE = 0.66$). The interaction between punishment and trial type was also statistically significant, ($b = -2.22$, $SE = 1.08$, 95% CIs [−4.36, −0.08]), $R^2_\beta = .04$. Simple effect tests revealed that the effect of punishment created the largest increase in ERP magnitude for the ERN ($b = 2.56$, $SE = 1.09$, 95% CIs [0.40, 4.72]), $R^2_\beta = .05$, and a smaller but still significant increase in amplitude for the CRN ($b = 0.72$, $SE = 0.28$, 95% CIs [0.18, 1.27]), $R^2_\beta = .05$; see Figure 4.

ΔERN. As with the traditional ERN analyses, self-reported phenomenology did not predict ΔERN scores; see Table 2. Secondly, we modeled the effect of punishment alone on the ΔERN. This model returned a significant main effect of punishment ($b = 2.32$, $SE = 1.10$, 95% CIs [0.13, 4.51]), $R^2_\beta = .04$, due to larger ΔERN amplitudes in the punished ($M = -21.38$ µV; $SE = 1.33$, 95% CI) than the unpunished ($M = -19.06$ µV; $SE = 1.26$) condition; see Figure 4.

Thus, while subjective phenomenology did not predict variation in any error-related ERP (ERN, ΔERN), both metrics demonstrated significant effects of punishment. These results indicate that neural monitoring processes are enhanced in the punished relative to the unpunished condition.[3]

2. In addition to the ERN, ERP studies of error monitoring also reveal a broader component that peaks 200–400 ms after errors at parietal electrodes. While this error positivity (Pe) been related to a number of psychological processes, the component is most reliably associated with conscious error awareness (cf. Wessel, 2012). We conducted a supplementary analysis on the Pe (operationalized as the mean amplitude 200–400 ms after the response at Pz) using a MLM structure identical to that used to analyze the ERN. In this model, we found a significant main effect of trial type ($b = -12.56$, $SE = 1.27$, 95% CIs [−15.11, −10.00]), $R^2_\beta = .71$, that did not interact with any phenomenological dimension. Additionally, there was a significant main effect of anxiety ($b = -1.32$, $SE = 0.59$, 95% CIs [−2.50, −0.14]), $R^2_\beta = .08$, suggesting that late ERP activity in general was reduced as subjective anxiety increased. When punishment was included, there were no additional new effects, including the main effect and interaction involving punishment. Thus, as with the ERN, it appears that phenomenology did not predict specific variation in error monitoring as indexed by the Pe.

3. Riesel et al. (2012) reported increased ERN amplitude with increasing trait anxiety. Therefore, it might be suggested that punishment will interact with subjective experience to predict ERN amplitude. However, when we ran additional analyses to test for this hypothesis, the interaction between subjective anxiety and punishment predicted neither the amplitude of the ERN ($b = -0.68$, $SE = 1.17$), 95% CIs [−3.00, 1.64] nor ΔERN ($b = -1.75$, $SE = 1.20$), 95% CIs [−4.12, 0.62]. No other interactions between other aspects of subjective experience (hopelessness, effort, frustration, or boredom) and punishment level predicted either the ERN or ΔERN. Thus, in the current data, we did not find evidence that subjective experience interacts with punishment condition to differentially predict neural error monitoring.

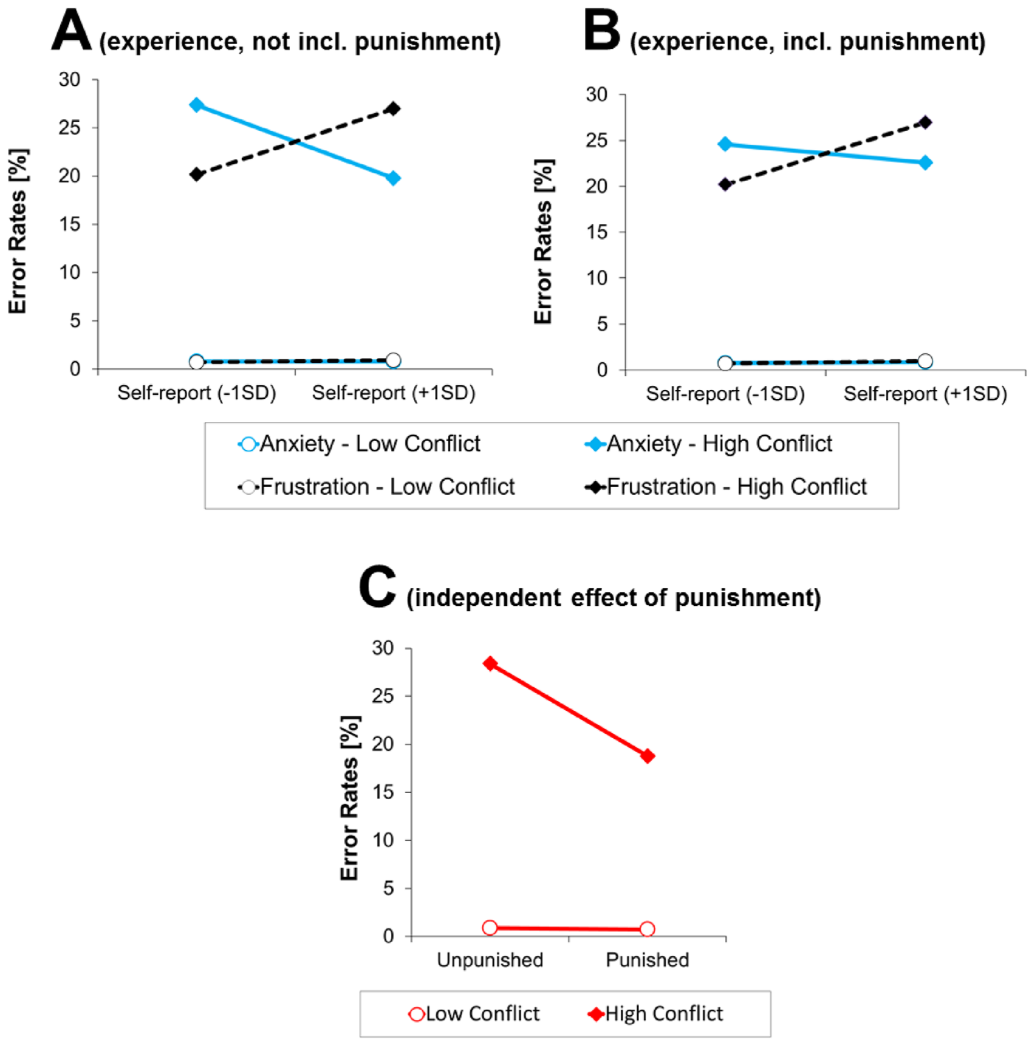

Figure 3. Line graphs depicting effects of punishment, frustration, and anxiety on percentage error rates. A: The effect of frustration (black) and anxiety (blue) on error rates without punishment as a covariate. B: The effect of frustration and nonsignificant effect of anxiety on error rates with punishment as a covariate. C: The effect of punishment on error rates. Subjective rating values 1 *SD* above and below the mean (zero due to centering) were used to generate the estimated marginal means.

Table 2. *Summary of MLM Results for the ERP Analyses (Significant Results in Bold)*

	ERPs by trial type				ΔERN			
Model without punishment	*b*	*SE*	95% CIs	R^2_β	*b*	*SE*	95% CIs	R^2_β
Trial type	**16.00**	**1.01**	**[13.97, 18.04]**	**.86**				
Anxiety	−0.21	0.80	[−1.79, 1.37]	< .01	−0.2	0.78	[−1.75, 1.35]	< .01
Anxiety*Trial type	−0.03	0.78	[−1.58, 1.51]	< .01				
Boredom	−0.90	0.82	[−2.52, 0.73]	< .01	−0.22	0.44	[−1.09, 0.65]	< .01
Boredom*Trial type	1.04	0.80	[−0.55, 2.64]	.02				
Effort	−1.58	1.10	[−3.75, 0.60]	.02	−1.34	1.01	[−3.35, 0.66]	.02
Effort*Trial type	1.61	1.07	[−0.52, 3.74]	.02				
Frustration	0.79	0.77	[−0.74, 2.31]	.01	1.05	0.75	[−0.43, 2.54]	.02
Frustration*Trial type	0.69	0.75	[−2.19, 0.80]	< .01				
Hopelessness	−0.12	1.00	[−2.10, 1.87]	< .01	−0.13	0.96	[−2.03, 1.78]	< .01
Hopelessness*Trial type	−0.02	0.98	[−1.96, 1.92]	< .01				
Model including punishment	*b*	*SE*	95% CIs	R^2_β	*b*	*SE*	95% CIs	R^2_β
Trial type	**17.26**	**1.19**	**[14.89, 19.63]**	**.86**				
Punishment	**2.94**	**1.1**	**[0.77, 5.12]**	**.10**	**2.32**	**1.1**	**[0.13, 4.51]**	**.04**
Punishment*Trial type	**−2.22**	**1.08**	**[−4.36, −0.08]**	**.04**				

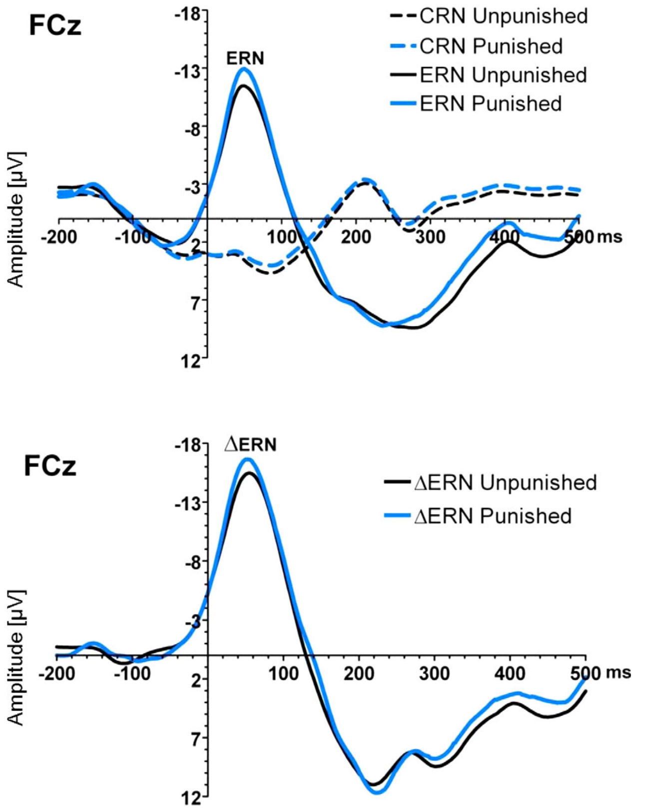

Figure 4. Response-locked ERPs depicted at electrode FCz. Upper: ERPs are depicted as a function of trial type (CRN: dashed lines, ERN: solid lines) and punishment condition (unpunished: black lines, punished: blue lines). Lower: ΔERN is depicted as a function of punishment.

Block-Level Analyses of Behavioral Data

Next, we analyzed the behavioral data at the level of the block (12 repeated measures) rather than quadrant (four repeated measures) to maximize the amount of within-participant variation in subjective experience in our data. Here, we only detail novel effects that arose at the block-level analysis that were not apparent at the quadrant level. However, full model statistics are presented in Table 3. Unless otherwise stated, simple effects tests of interactions that were also significant at the quadrant level of analysis revealed the same pattern of statistical significance at the block level.

Choice error rates. An initial model—not including punishment as a factor—revealed results that were highly similar to those observed at the quadrant resolution (significant main effects: conflict level, anxiety, frustration; significant interactions: Conflict Level × Anxiety, Conflict Level × Frustration); see Table 3 for details. Interestingly, the block-level analysis also revealed a number of effects that were not apparent in the subsection analyses. Increases in self-reported effort were associated with reduced overall error rates ($b = -2.81$, $SE = 0.75$, 95% CIs [−4.27, −1.34]), $R^2_\beta = .03$, and this main effect further interacted with conflict level ($b = 2.69$, $SE = 0.77$, 95% CIs [1.19, 4.19]), $R^2_\beta = .03$. Follow-up simple effects tests revealed that this was due to increasing effort predicting reduced error rates on high-conflict trials ($b = -2.81$, $SE = 0.75$, 95% CIs [−4.27, −1.34]), $R^2_\beta = .03$, whereas low-conflict trials were not associated with subjective effort ($b = -0.12$, $SE = 0.80$, 95% CIs [−0.21, 0.06]), $R^2_\beta < .01$. Finally, choice error rates also increased with increasing self-reported hopelessness ($b = 1.85$, $SE = 0.64$, 95% CIs [0.58, 3.12]), $R^2_\beta = .02$, and this effect further interacted with conflict level ($b = -1.92$, $SE = 0.66$, 95% CIs [−3.22, −0.62]), $R^2_\beta = .02$, due to increasing error rates on high-conflict trials ($b = 1.85$, $SE = 0.64$, 95% CIs [0.58, 3.11]), $R^2_\beta = .02$, but not low-conflict trials, ($b = -0.07$, $SE = 0.07$, 95% CIs [−0.21, 0.06]), $R^2_\beta < .01$, with elevated levels of subjective hopelessness.[4]

Next, we added punishment to this model. As with the previous analyses, all effects involving subjective anxiety were no longer significant, while the main effects of effort, hopelessness, punishment, and frustration, as well as the interactions between conflict level and frustration, effort, hopelessness, and punishment remained significant in this model; see Figure 5.

In summary, this block-level analysis largely replicated the results from the quadrant-level resolution, and found additional effects of hopelessness and effort on choice error rates. More specifically, while high-conflict error rates increased as a function of increasing within-subject hopelessness, subjective effort predicted reduced error rates on these infrequent, control-demanding trials.

Mean RT. As with the prior analyses, the initial phenomenology-focused model revealed main effects of conflict level and boredom, in addition to interactions between conflict level and both frustration and anxiety; see Table 1. Conflict level also interacted with subjective boredom ($b = -3.94$, $SE = 1.89$, 95% CIs [−7.65, −0.22]), $R^2_\beta = .01$. This was due to longer RTs with increasing subjective levels of boredom on high-conflict ($b = 4.20$, $SE = 1.63$, 95% CIs [1.00, 7.40]), $R^2_\beta = .01$, but not low-conflict trials ($b = 0.27$, $SE = 1.17$, 95% CIs [−2.04, 2.57]), $R^2_\beta < .01$.

We then added the punishment factor to the model; all previous effects remained significant, with the exception of main effects and interaction involving anxiety, and the interaction between conflict level and boredom. As with the quadrant-level analysis, this model also revealed a main effect of punishment, which further interacted with conflict level; see Table 3.

As with the choice error rates, these block-level analyses largely replicated the RT effects observed at the quadrant level, with one additional interaction between self-reported boredom and conflict level. As this novel interaction was only significant in a single model, and was no longer apparent when we accounted for punishment, this interaction is not discussed further. More interestingly, however, we observed no effects of hopelessness or effort on RT performance. Thus, the earlier association between these phenomenological experiences and choice error rates cannot be accounted for by a simple speed-accuracy trade-off, and, instead, most likely reflect variation in the execution of inhibitory control.

Discussion

We investigated the phenomenology of performance monitoring and cognitive control. Interestingly, effective and ineffective

4. The temporal dynamics of these effects could also be investigated by predicting current performance from the experience reported on the previous block. Such an analysis might give insight into the causal relationship between emotion and control (e.g., does anxiety on the previous block predict increased control on the current block?). However, when we conducted this analysis, we did not find that previous block experience predicted choice error rates when we controlled for experience on the current trial. Thus, the experience reported for the current block is a better predictor of current block performance than the emotion that relates to the previous block, and we acknowledge the correlational—rather than directional—nature of our results.

Table 3. *Summary of MLM Results for the Block-Level Analyses (Significant Results in Bold)*

	Reaction time				Choice error rates			
Model without punishment	*b*	*SE*	95% CIs	R^2_β	b	SE	95% CIs	R^2_β
Conflict level	**−106.52**	**4.85**	**[−116.31, −96.73]**	**.92**	**−22.85**	**1.95**	**[−26.78, −18.92]**	**.77**
Anxiety	−0.40	1.59	[−3.52, 2.72]	< .01	**−2.33**	**0.54**	**[−3.39, −1.27]**	**.04**
Anxiety*Conflict level	**4.45**	**1.84**	**[0.83, 8.07]**	**.01**	**2.32**	**0.56**	**[1.23, 3.41]**	**.04**
Boredom	**4.20**	**1.63**	**[1.00, 7.41]**	**.01**	0.33	0.55	[−0.76, 1.41]	< .01
Boredom*Conflict level	**−3.94**	**1.89**	**[−7.65, −0.22]**	**.01**	−0.34	0.57	[−1.46, 0.78]	< .01
Effort	−0.68	2.19	[−4.98, 3.63]	< .01	**−2.81**	**0.75**	**[−4.27, −1.34]**	**.03**
Effort*Conflict level	1.48	2.54	[−3.51, 6.47]	< .01	**2.69**	**0.77**	**[1.19, 4.19]**	**.03**
Frustration	2.47	1.41	[−0.29, 5.23]	< .01	**3.82**	**0.48**	**[2.88, 4.76]**	**.13**
Frustration*Conflict level	**−7.57**	**1.63**	**[−10.78, −4.37]**	**.05**	**−3.78**	**0.49**	**[−4.74, −2.81]**	**.11**
Hopelessness	0.10	1.91	[−3.65, 3.85]	< .01	**1.85**	**0.64**	**[0.58, 3.12]**	**.02**
Hopelessness*Conflict level	−0.92	2.21	[−5.26, 3.42]	< .01	**−1.92**	**0.66**	**[−3.22, −0.62]**	**.02**
Model including punishment	*b*	*SE*	95% CIs	R^2_β	*b*	*SE*	95% CIs	R^2_β
Conflict level	**−106.53**	**4.85**	**[−116.33, 96.74]**	**.92**	**−22.86**	**1.95**	**[−26.79, −18.93]**	**.77**
Anxiety	−1.04	1.72	[−4.41, 2.33]	< .01	−0.47	0.54	[−1.52, 0.58]	< .01
Anxiety*Conflict level	2.10	1.97	[−1.78, 5.97]	< .01	0.48	0.56	[−0.61, 1.57]	< .01
Boredom	**4.42**	**1.64**	**[1.19, 7.66]**	**.02**	−0.31	0.51	[−1.32, 0.70]	< .01
Boredom*Conflict level	−3.14	1.89	[−6.85, 0.58]	< .01	0.28	0.53	[−0.76, 1.32]	< .01
Effort	−0.80	2.19	[−5.11, 3.51]	< .01	**−2.43**	**0.69**	**[−3.78, −1.08]**	**.03**
Effort*Conflict level	1.00	2.52	[−3.95, 5.95]	< .01	**2.32**	**0.71**	**[0.92, 3.71]**	**.02**
Frustration	2.45	1.41	[−0.31, 5.21]	< .01	**3.86**	**0.44**	**[2.99, 4.73]**	**.15**
Frustration*Conflict level	**−7.63**	**1.61**	**[−10.80, −4.46]**	**.05**	**−3.82**	**0.45**	**[−4.71, −2.93]**	**.13**
Hopelessness	0.14	1.91	[−3.61, 3.88]	< .01	**1.72**	**0.59**	**[0.56, 2.89]**	**.02**
Hopelessness*Conflict level	−0.76	2.18	[−5.05, 3.53]	< .01	**−1.8**	**0.61**	**[−3.00, −0.60]**	**.02**
Punishment	1.78	1.82	[−1.79, 5.36]	.04	**−5.21**	**0.57**	**[−6.33, −4.09]**	**.16**
Punishment*Conflict level	**6.59**	**2.09**	**[2.48, 10.69]**	**.02**	**5.16**	**0.59**	**[4.00, 6.31]**	**.14**

cognitive control were associated with divergent subjective experiences. Across both resolutions of experiential analysis (i.e., quadrant and block level), increased subjective frustration was associated with behavior dominated by the prepotent response tendency, while anxiety demonstrated the opposite profile, accompanying elevated response caution. When analyses accounted for changes in experience at the lowest temporal resolution available in our data (i.e., at the block level), subjective effort predicted increased inhibitory control, while hopelessness was associated with poorer regulation of the prepotent response tendency. Clarifying the nature of these phenomenological correlates of control,

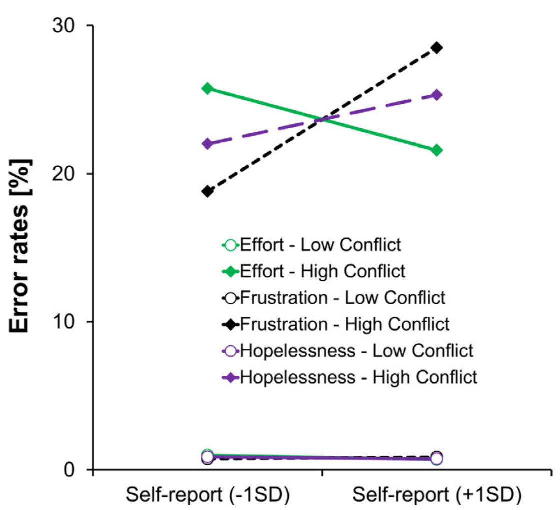

Figure 5. Line graphs depicting error rates in the block-level analyses as a function of effort (green solid line), frustration (black short dash), and hopelessness (purple long dash) while controlling for the effects of punishment. Subjective rating values 1 *SD* above and below the mean (zero due to centering) were used to generate estimated marginal means.

frustration, effort, and hopelessness—but not anxiety—predicted performance after controlling for the effects of punishment. In contrast, while punishment increased neurophysiological reactivity to errors (ΔERN), our ERP results were not associated with self-reported phenomenology.

Phenomenology of Control Implementation

Our results contribute to emerging views that affect and motivation are closely related to variation in cognitive control (Braver et al., 2014; Inzlicht et al., 2015; Pessoa, 2009; Saunders, Milyavskaya, & Inzlicht, 2015). Most significantly, while existing studies have proposed that control-demanding situations are negatively valenced (Aarts et al., 2013; Botvinick, 2007; Dreisbach & Fisher, 2012), our results indicate that experiences with shared valence predict different aspects of control implementation. Thus, as with emotional experience more broadly (Barrett, 2013), our results suggest that feelings arising during controlled performance are both heterogeneous and related to the objective efficacy of goal-directed actions.

Fluctuating anxiety was more strongly related to our punishment manipulation than any other experience. Indeed, the initial positive association between anxiety levels and inhibitory control was subsumed by an analogous effect of punishment in a second model. This shared variance between punishment, control, and anxious phenomenology is highly consistent with the putative neuropsychology of anxiety. In particular, anxiety has been related to an adaptive mechanism termed the Behavioral Inhibition System (BIS; Gray & McNaughton, 2000). Here, anxiety is born out of conflicts either between (e.g., approach vs. avoid) or within (e.g., approach vs. approach) motivational orientations (see also Corr, 2008; Hirsh, Mar, & Peterson, 2012). Anxiety might arise when an organism experiences conflict between the desire to approach a situation (e.g., perform the control task well) and the urge to avoid a source of threat (e.g., avoid the aversive sound blast). In such situations—where neither motivational drive can be completely satisfied—BIS putatively drives increased attention and arousal, as well as the downregulation of prepotent responding (Gray & McNaughton, 2000). Thus, our results are consistent with a view that anxiety and punishment sensitivity arise out of a common motivational locus, intimately related to reducing impulsive responses.

In contrast to threat-related phenomena (i.e., self-reported anxiety and external punishment), self-reported frustration was associated with less goal-conducive, impulsive behaviors. As an emotion, frustration is characterized by a lack of gratification and a number of impulsive tendencies that can be viewed as the antithesis of self-regulation, such as interpersonal aggression (Berkowitz, 1989; Bushman et al., 2014; Harmon-Jones & Allen, 1998). While it is unlikely that our participants experienced the acute frustration associated with aggression, it seems parsimonious to suggest that frustration might be closely linked to motivational states related to impulsive behaviors across multiple domains, such as RT speeding, yielding to prepotent responses and aggression.

At the block-level, subjective effort and hopelessness predicted improved and impaired inhibitory control, respectively. As these experiences did not predict RTs, the results are not attributable to a speed-accuracy trade-off. Interestingly, feelings of hopelessness have been associated with the adequate ability to define goals, combined with a real or perceived inability to execute goal-relevant behaviors (Hadley & MacLeod, 2010; Melges & Bowlby, 1969). For example, a dieter who sets the goal to lose weight may experience hopelessness if he/she feels unable to resist unhealthy temptations. Therefore, the observed reduction in inhibitory control is consistent with the putative motivational implications of hopelessness, and also accords with previous suggestions that perceived self-efficacy (Bandura, 1982) and beliefs about the capacity to implement control (Job, Dweck, & Walton, 2010) are associated with goal achievement. Conversely, inhibitory control improved when participants reported increased effort. Considered together, these findings suggest that individuals develop a strong sense of the effectiveness of actions, and that these feelings are systematically associated with objective measures of control.

Negative Affect and Performance Monitoring

Our ERP results replicate previous findings that the threat of punishment by a primary reinforcer leads to increased performance monitoring (cf. Riesel et al., 2012) and, more generally, that the ERN reflects the subjective value of performance (e.g., Endrass et al., 2010; Hajcak, Moser, Yeung, & Simons, 2005; Legault & Inzlicht, 2013; Pailing & Segalowitz, 2004; Stürmer, Nigbur, Schacht, & Sommer, 2011; Wiswede, Münte, & Rüsseler, 2009).

Unlike overt behavior, however, the ERN was not associated with any specific phenomenology. This finding differs from recent findings that the ACC is sensitive to both performance monitoring and phenomenology during control (Spunt et al., 2012). While several differences existed between the previous study and our own, dissimilarities between the EEG and fMRI signal perhaps represent the largest discrepancy between investigations. While the fMRI signal develops over a number of seconds, potentially reflecting slowly developing cognitive processes (Logothetis, 2008), ERPs reflect rapidly occurring neural signals, phase-locked to the event of interest. The ERN in particular dissipates very soon after mistakes, potentially preceding conscious error awareness (Nieuwenhuis et al., 2001). Thus, the fMRI signal is perhaps sensitive to slower emotion-related activity that does not develop within the short time course of the ERN.

From our results alone, however, it is likely inaccurate to suggest that early neural monitoring is not sensitive to affect, as several studies have reported associations between the ERN and canonically affective phenomena, such as affective priming (Aarts et al., 2013), the misattribution of arousal (Inzlicht & Al-Khindi, 2012), cognitive reappraisal of emotion (Hobson, Saunders, Al-Khindi, & Inzlicht, 2014), or the induction of short-term negative affect (Wiswede, Münte, Goschke, & Rüsseler, 2009). Thus, the ERN may reflect an initial evaluation that determines whether actions are "good" or "bad," without containing the richer information that manifests later as consciously accessible experience.

Integration of Emotion, Phenomenology, and Cognitive Control

It is also important to consider how our phenomenological results can be integrated with existing affective and computational accounts of control. First, it should be noted that affective, computational, and phenomenological accounts need not be mutually exclusive (cf. Koban & Pourtois, 2014; Shackman et al., 2012). However, as computational, affective, and phenomenological results occupy varying levels of analytical specificity (see also Spunt et al., 2012), it is important to ask what a comprehensive account of control (i.e., one that recognizes all levels of analysis) might look like. Recently, it has been proposed that such integration might be achieved by considering control in light of the basic psychological and biological components that putatively underlie emotion (Inzlicht et al., 2015). Here, so-called basic emotions (frustration, anxiety, and so on) emerge from the combined activity of several more elemental processes, such as core affect (i.e., valence and arousal), emotional expressions, physiology, cognitive processes (e.g., attribution, appraisal), and subjective experience (cf. Barrett, 2006; Coan, 2010; Russell, 2003).

Indeed, mounting evidence suggests that similar core processes are apparent in cognitive control. First, while the computational starting point for control might remain the detection of conflict (Botvinick et al., 2001), this conflict appears to be negatively valenced (Aarts et al., 2013; Driesbach & Fisher, 2012) and is accompanied by increased peripheral arousal (e.g., Hajcak et al., 2003). Furthermore, recent evidence suggests that control is systematically modulated by established cognitive moderators of emotion (Hobson et al., 2014; Inzlicht & Al-Khindi, 2012) and individual differences that increase or decrease the ability to monitor internal affective signals (de Galan, Sellaro, Colzato, & Hommel, 2014; Teper & Inzlicht, 2013). Thus, rather than challenging the cognitive architecture of control, our results suggest that different behavioral outcomes arising from these central control mechanisms (e.g., ineffective inhibitory control, reduced response caution) are accompanied by divergent subjective experiences (e.g., hopelessness, frustration). Crucially, this suggestion is consistent with views that control and emotion both are emergent features of common processes that underlie goal-directed action (cf. Inzlicht et al., 2015).

Our phenomenological analyses should be considered with an important caveat: we are currently unable to address the causal relationship between experience and control. At present, it seems parsimonious to suggest that control-related experiences are associated with motivational states that either help or hinder performance. However, due to the correlational nature of our data, it is unclear whether feelings initiate a given task orientation (e.g., frustration drives reduced caution), or if phenomenological experiences emerge as a consequence of behavioral efficacy or changes in motivational state (e.g., ineffective control leads to increased hopelessness). As varying accounts of the functionality of emotions are present across affective science (e.g., Barrett, 2013; Ekman, 1992; Keltner & Gross, 1999; Levenson, 1994; Russell, 2003), this challenge is certainly not unique to the current study. However, one important question for future research might be to examine the functional significance of subjective experiences in control. For example, will different behavioral outcomes arise when task contexts promote frustration, hopelessness, or anxiety?

Limitations and Future Directions

Our study has several limitations that merit consideration. First, our participants reported subjective experience after every block. While this allowed us to track fluctuating experience with greater fidelity than the one-off administration of a self-report scale, our procedure nevertheless measured fluctuations in feelings at the resolution of minutes, rather than seconds or milliseconds. Future research might benefit from measuring control-related experience at a finer temporal resolution, perhaps even at the level of a single trial. However, while such a procedure has an intuitive appeal, pragmatic concerns limit the ability to measure highly transient experiential states by explicit self-report. As noted by Spunt et al. (2012), having participants report their affective experience at the single trial level would be highly disruptive to ongoing performance. Thus, the temporal resolution of subjective reporting in the current study was determined to balance temporal sensitivity with the ability to generate reliable control measures.

Second, while our study is the first to demonstrate that within-participant variation in affect tracks inhibitory control, further experiential analyses could use phenomenological analyses to advance both theoretical and individual difference accounts of control. For example, in addition to the inhibitory control measures operationalized in the current study, online control adjustments are observed in the form of trial-to-trial conflict adaptation (Gratton, Coles, & Donchin, 1992) and post-error slowing (Rabbitt & Rodgers, 1977). As these sequential effects are suggested to arise from a single conflict-control loop (Botvinick et al., 2001), future research might test if these control phenomena are associated with a common subjective experience. Finally, various psychopathologies have also been associated with changes in cognitive control and performance monitoring (e.g., Saunders & Jentzsch, 2014; Weinberg et al., 2012; Zeier, Baskin-Sommers, Hiatt Racer, & Newman, 2012), with alterations in emotional processing identified as a candidate mechanism through which these changes in cognitive control might arise (e.g., Roiser & Sahakian, 2012). Thus, future research tracking within participant phenomenology during control performance might provide useful insights into these maladaptive processes in clinical samples.

Conclusion

The results of the current study indicate not only that controlled performance is associated with a number of different feelings, but also that divergent subjective experiences predict effective and ineffective aspects of control, including variation in response caution (i.e., anxiety and frustration) and the exertion of inhibitory control (i.e., subjective effort and hopelessness). These results provide a more nuanced account of the relationship between emotional processing and cognitive control, promising that the continued investigation of phenomenology might shed light on so-called emotion-cognition interactions across multiple domains in psychological science.

References

Aarts, K., De Houwer, J., & Pourtois, G. (2013). Erroneous and correct actions have a different affective valence: Evidence from ERPs. *Emotion*, *13*, 960–973. doi: 10.1037/a0032808

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*, 122–147. doi: 10.1037/0003-066X.37.2.122

Banich, M. T. (2009). Executive function: The search for an integrated account. *Current Directions in Psychological Science*, *18*, 89–94. doi: 10.1016/S0021-9924(03)00019-4

Barrett, L. F. (2006). Are emotions natural kinds? *Perspectives on Psychological Science*, *1*, 28–58. doi: 10.1111/j.1745-6916.2006.00003.x

Barrett, L. F. (2013). Psychological construction: The Darwinian approach to the science of emotion. *Emotion Review*, *5*, 379–389. doi: 10.1177/1754073913489753

Barrett, L. F., Mesquita, B., Ochsner, K. N., & Gross, J. J. (2007). The experience of emotion. *Annual Review of Psychology*, *58*, 373–403. doi: 10.1146/annurev.psych.58.110405.085709

Berkowitz, L. (1989). Frustration-aggression hypothesis: Examination and reformulation. *Psychological Bulletin*, *106*, 59–73. doi: 10.1037/0033-2909.106.1.59

Botvinick, M. M. (2007). Conflict monitoring and decision making: Reconciling two perspectives on anterior cingulate function. *Cognitive Affective & Behavioral Neuroscience*, *7*, 356–366. doi: 10.3758/CABN.7.4.356

Botvinick, M. M., Braver, T. S., Barch, D. M., Carter, C. S., & Cohen, J. D. (2001). Conflict monitoring and cognitive control. *Psychological Review*, *108*, 624–652. doi: 10.1037/0033-295X.108.3.624

Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences*, *16*, 106–113. doi: 10.1016/j.tics.2011.12.010

Braver, T. S., Krug, M. K., Chiew, K. S., Kool, W., Westbrook, J. A., Clement, N. J., . Somerville, L. H. (2014). Mechanisms of motivation–cognition interaction: Challenges and opportunities. *Cognitive, Affective, & Behavioral Neuroscience*, *14*, 443–472. doi: 10.3758/s13415-014-0300-0

Bushman, B. J., DeWall, C. N., Pond, R. S., & Hanus, M. D. (2014). Low glucose relates to greater aggression in married couples. *Proceedings of the National Academy of Sciences*, *111*, 6254–6257. doi: 10.1073/pnas.1400619111

Cavanagh, J. F., & Shackman, A. J. (2014). Frontal midline theta reflects anxiety and cognitive control: Meta-analytic evidence. *Journal of Physiology–Paris*. doi: 10.1016/j.jphysparis.2014.04.003

Critchley, H. D., Tang, J., Glaser, D., Butterworth, B., & Dolan, R. J. (2005). Anterior cingulate activity during error and autonomic response. *NeuroImage*, *27*, 885–895. doi: 10.1016/j.neuroimage.2005.05.047

Coan, J. A. (2010). Emergent ghosts of the emotion machine. *Emotion Review*, *2*, 274–285. doi: 10.1177/1754073910361978

Corr, P. J. (2008) *The reinforcement sensitivity theory of personality*. Cambridge, MA: Cambridge Univerity Press.

Cumming, G. (2013). The new statistics: Why and how. *Psychological Science*, *25*, 7–29. doi: 10.1177/0956797613504966

de Galan, M., Sellaro, R., Colzato, L. S., & Hommel, B. (2014). Conflict adaptation is predicted by the cognitive, but not the affective alexithymia dimension. *Frontiers in Psychology*, *5*, 768. doi: 10.3389/fpsyg.2014.00768

Dehaene, S., Posner, M. I., & Tucker, D. M. (1994). Localization of a neural system for error-detection and compensation. *Psychological Science*, *5*, 303–305. doi: 10.1111/j.1467-9280.1994.tb00630.x

Dreisbach, G., & Fischer, R. (2012). Conflicts as aversive signals. *Brain and Cognition*, *78*, 94–98. doi: 10.1016/j.bandc.2011.12.003

Edwards, L. J., Muller, K. E., Wolfinger, R. D., Qaqish, B. F., & Schabenberger, O. (2008). An R2 statistic for fixed effects in the linear mixed model. *Statistics in Medicine*, *27*, 6137–6157. doi: 10.1002/sim.3429

Ekman, P. (1992). An argument for basic emotions. *Cognition & Emotion*, *6*, 169–200. doi: 10.1080/02699939208411068

Endrass, T., Schuermann, B., Kaufmann, C., Spielberg, R., Kniesche, R., & Kathmann, N. (2010). Performance monitoring and error significance in patients with obsessive-compulsive disorder. *Biological Psychology*, *84*, 257–263. doi: 10.1016/j.biopsycho.2010.02.002

Falkenstein, M., Hohnsbein, J., Hoormann, J., & Blanke, L. (1991). Effects of crossmodal divided attention on late ERP components. II. Error processing in choice reaction tasks. *Electroencephalography and Clinical Neurophysiology*, *78*, 447–455. doi: 10.1016/0013-4694(91)90062-9

Gehring, W. J., Goss, B., Coles, M. G. H., Meyer, D. E., & Donchin, E. (1993). A neural system for error-detection and compensation. *Psychological Science*, *4*, 385–390. doi: 10.1111/j.1467-9280.1994.tb00630.x

Gratton, G., Coles, M. G., & Donchin, E. (1983). A new method for off-line removal of ocular artifact. *Electroencephalography and Clinical Neurophysiology*, *55*, 468–484. doi: 10.1016/0013-4694(83)90135-9

Gratton, G., Coles, M. G., & Donchin, E. (1992). Optimizing the use of information: Strategic control of activation of responses. *Journal of Experimental Psychology: General*, *121*, 480–506. doi: 10.1037//0096-3445.121.4.480

Gray, J. A., & McNaughton, N. (2000) *The neuropsychology of anxiety: An enquiry into the functions of the septo-hippocampal system*. Oxford, UK: Oxford University Press.

Gross, J. J., & Jazaieri, H. (2014). Emotion, emotion regulation, and psychopathology: An affective science perspective. *Clinical Psychological Science*, *2*, 387–401. doi: 10.1177/2167702614536164

Hadley, S. A., & MacLeod, A. K. (2010). Conditional goal-setting, personal goals and hopelessness about the future. *Cognition and Emotion*, *24*, 1191–1198. doi: 10.1080/02699930903122521

Hajcak. G., McDonald, N., & Simons, R. (2003). To err is autonomic: Error-related brain potentials, ANS activity, and post-error compensatory behavior. *Psychophysiology*, *40*, 895–903. doi: 10.1111/1469-8986.00107

Hajcak, G., Moser, J. S., Yeung, N., & Simons, R. F. (2005). On the ERN and the significance of errors. *Psychophysiology*, *42*, 151–160. doi: 10.1111/j.1469-8984.2005.00270.x

Harmon-Jones, E., & Allen, J. J. (1998). Anger and frontal brain activity: EEG asymmetry consistent with approach motivation despite negative affective valence. *Journal of Personality and Social Psychology*, *74*, 1310–1316. doi: 10.1037//0022-3514.74.5.1310

Hengstler, M., Holland, R. W., van Steenbergen, H., & van Knippenberg, A. (2014). The influence of approach–avoidance motivational orientation on conflict adaptation. *Cognitive, Affective, & Behavioral Neuroscience*, *14*, 548–560. doi: 10.3758/s13415-014-0295-6

Hirsh, J. B., Mar, R. A., & Peterson, J. B. (2012). Psychological entropy: A framework for understanding uncertainty-related anxiety. *Psychological Review*, *119*, 304–320. doi: 10.1037/a0026767

Hobson, N., Saunders, B., Inzlicht, M., & Al-Khindi, T. (2014). Emotional down-regulation diminishes cognitive control. *Emotion*, *6*, 1014–1026. doi: 10.1037/a0038028

Holroyd, C. B., & Coles, M. G. H. (2002). The neural basis of human error processing: Reinforcement learning, dopamine, and the error-related negativity. *Psychological Review*, *109*, 679–709. doi: 10.1037/0033-295X.109.4.679

Husserl, E. (1983/1913). *Ideas pertaining to a pure phenomenology and to a phenomenological philosophy. (F. Kersten, Trans.)*. The Hague, The Netherlands: Martinus Nijhoff Publishers.

Inzlicht, M., & Al-Khindi, T. (2012). ERN and the placebo: A misattribution approach to studying the arousal properties of the error-related negativity. *Journal of Experimental Psychology: General*, *141*, 799–807. doi: 10.1037/a0027586

Inzlicht, M., Bartholow, B. D., & Hirsch, J. B. (2015). Emotional foundations of cognitive control. *Trends in Cognitive Sciences*, *19*, 126–132. doi: 10.1016/j.tics.2015.01.004

Job, V., Dweck, C. S., & Walton, G. M. (2010). Ego depletion—Is it all in your head? Implicit theories about willpower affect self-regulation. *Psychological Science*, *21*, 1686–1693. doi: 10.1177/0956797610384745

Jones, A. D., Cho, R. Y., Nystrom, L. E., Cohen, J. D., & Braver, T. S. (2002). A computational model of anterior cingulate function in speeded response tasks: Effects of frequency, sequence, and conflict. *Cognitive, Affective, & Behavioral Neuroscience*, *2*, 300–317. doi: 10.3758/CABN.2.4.300

Keltner, D., & Gross, J. J. (1999). Functional accounts of emotions. *Cognition & Emotion*, *13*, 467–480. doi: 10.1080/026999399379140

Koban, L., Corradi-Dell'Acqua, C., & Vuilleumier, P. (2013). Integration of error agency and representation of others' pain in the anterior insula. *Journal of Cognitive Neuroscience*, *25*, 258–272. doi: 10.1162/jocn_a_00324

Koban, L., & Pourtois, G. (2014). Brain systems underlying the affective and social monitoring of actions: An integrative review. *Neuroscience & Biobehavioral Reviews*, *46*, 71–84. doi: 10.1016/j.neubiorev.2014.02.014

Legault, L., & Inzlicht, M. (2013). Self-determination, self-regulation, and the brain: Autonomy improves performance by enhancing neuroaffective responsiveness to self-regulation failure. *Journal of Personality and Social Psychology*, *105*, 123–138. doi: 10.1037/a0030426

Levenson, R. W. (1994). Human emotion: A functional view. In P. Ekman & R. J. Davidson (Eds.), *The nature of emotion: Fundamental questions* (pp. 123–126). New York, NY: Oxford University Press.

Lindström, B. R., Mattson-Ma˚rn, I. B., Golkar, A., & Olsson, A. (2013). In your face: risk of punishment enhances cognitive control and error-related activity in the corrugator supercilii muscle. *PLOS ONE*, *49*, 560–567. doi: 10.1371/journal.pone.0065692

Logothetis, N. K. (2008). What we can do and what we cannot do with fMRI. *Nature*, *453*, 869–878. doi: 10.1038/nature06976

Melges, F. T., & Bowlby, J. (1969). Types of hopelessness in psychopathological process. *Archives of General Psychiatry*, *20*, 690–699.

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. *Cognitive Psychology*, *41*, 49–100. doi: 10.1006/cogp.1999.0734

Nieuwenhuis, S., Ridderinkhof, K. R., Blom, J., Band, G. P., & Kok, A. (2001). Error-related brain potentials are differentially related to awareness of response errors: Evidence from an antisaccade task. *Psychophysiology*, *38*, 752–760. doi: 10.1017/S0048577201001111

Olvet, D. M., & Hajcak, G. (2009). The stability of error-related brain activity with increasing trials. *Psychophysiology*, *46*, 957–961. doi: 10.1111/j.1469-8986.2009.00848.x

Pailing, P. E., & Segalowitz, S. J. (2004). The error-related negativity as a state and trait measure: Motivation, personality, and ERPs in response to errors. *Psychophysiology*, *41*, 84–95. doi: 10.1111/1469-8986.00124

Pessoa, L. (2009). How do emotion and motivation direct executive control? *Trends in Cognitive Sciences*, *13*, 160–166. doi: 10.1016/j.tics.2009.01.006

Rabbitt, P., & Rodgers, B. (1977). What does a man do after he makes an error? An analysis of response programming. *Quarterly Journal of Experimental Psychology*, *29*, 727–743. doi: 10.1080/14640747708400645

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (Vol. *1*). New York, NY: Sage.

Riesel, A., Weinberg, A., Endrass, T., Kathmann, N., & Hajcak, G. (2012). Punishment has a lasting impact on error-related brain activity. *Psychophysiology*, *49*, 239–247. doi: 10.1111/j.1469-8986.2011.01298.x

Roiser, J. P., & Sahakian, B. J. (2013). Hot and cold cognition in depression. *CNS Spectrums*, *18*, 139–149. doi: 10.1017/S1092852913000072

Ruchsow, M., Herrnberger, B., Wiesend, C., Grön, G., Spitzer, M., & Kiefer, M. (2004). The effect of erroneous responses on response monitoring in patients with major depressive disorder: A study with event-related potentials. *Psychophysiology*, *41*, 833–840. doi: 10.1111/j.1469-8986.2004.00237.x

Russell, J. A. (2003). Core affect and the psychological construction of emotion. *Psychological Review*, *110*, 145–172. doi: 10.1037/0033-295X.110.1.145

Saunders, B., & Jentzsch, I. (2014). Reactive and proactive control adjustments under increased depressive symptoms: Insights from the classic and emotional-face Stroop task. *Quarterly Journal of Experimental Psychology*, *67*, 884–898. doi: 10.1080/17470218.2013.836235

Saunders, B., Milyavskaya, M., & Inzlicht, M. (2015). Variation in cognitive control as emotion regulation. *Psychological Inquiry*, *26*, 108–115. doi: 10.1080/1047840X.2015.962396

Schouppe, N., De Houwer, J., Ridderinkhof, R. K., & Notebaert, W. (2012). Conflict: Run! Reduced Stroop interference with avoidance responses. *Quarterly Journal of Experimental Psychology*, *65*, 1052–1058. doi: 10.1080/17470218.2012.685080

Schrijvers, D., de Bruijn, E. R., Maas, Y., De Grave, C., Sabbe, B. G., & Hulstijn, W. (2008). Action monitoring in major depressive disorder with psychomotor retardation. *Cortex*, *44*, 569–579. doi: 10.1016/j.cortex.2007.08.014

Shackman, A. J., Salomons, T. V., Slagter, H. A., Fox, A. S., Winter, J. J., & Davidson, R. J. (2011). The integration of negative affect, pain and cognitive control in the cingulate cortex. *Nature Reviews Neuroscience*, *12*, 154–167. doi: 10.1038/nrn2994

Spunt, R. P., Lieberman, M. D., Cohen, J. R., & Eisenberger, N. I. (2012). The phenomenology of error-processing: The dorsal ACC response to stop-signal errors tracks reports of negative affect. *Journal of Cognitive Neuroscience*, *24*, 1753–1765. doi: 10.1162/jocn_a_00242

Stürmer, B., Nigbur, R., Schacht, A., & Sommer, W. (2011). Reward and punishment effects on error processing and conflict control. *Frontiers in Psychology*, *2*. doi: 10.3389/fpsyg.2011.00335

Teper, R., & Inzlicht, M. (2013). Meditation, mindfulness, and executive control: The importance of emotional acceptance and brain-based performance monitoring. *Social Cognitive Affective Neuroscience*, *8*, 85–92. doi: 10.1093/scan/nss045

Weinberg, A., Riesel, A., & Hajcak, G. (2012). Integrating multiple perspectives on error-related brain activity: The ERN as a neural indicator of trait defensive reactivity. *Motivation and Emotion*, *36*, 84–100. doi: 10.1007/s11031-011-9269-y

Wessel, J. R. (2012). Error awareness and the error-related negativity: Evaluating the first decade of evidence. *Frontiers in Human Neuroscience*, *6*. doi: 10.3389/fnhum.2012.00088

Wiswede, D., Münte, T. F., Goschke, T., & Rüsseler, J. (2009). Modulation of the error-related negativity by induction of short-term negative affect. *Neuropsychologia*, *47*, 83–90. doi: 10.1016/j.neuropsychologia.2008.08.016

Wiswede, D., Münte, T. F., Krämer, U. M., & Rüsseler, J. (2009). Embodied emotion modulates neural signature of performance monitoring. *PLOS ONE*, *4*, e5754. doi: 10.1371/journal.pone.0005754

Wiswede, D., Münte, T. F., & Rüsseler, J. (2009). Negative affect induced by derogatory verbal feedback modulates the neural signature of error detection. *Social Cognitive and Affective Neuroscience*, *4*, 227–237. doi: 10.1093/scan/nsp015

Yeung, N., Botvinick, M. M., & Cohen, J. D. (2004). The neural basis of error detection: conflict monitoring and the error-related negativity. *Psychological Review*, *111*, 931–959. doi: 10.1037/0033-295x.111.4.931

Zeier, J. D., Baskin-Sommers, A. R., Hiatt Racer, K. D., & Newman, J. P. (2012). Cognitive control deficits associated with antisocial personality disorder and psychopathy. *Personality Disorders: Theory, Research, and Treatment*, *3*, 283–293. doi: 10.1037/a0023137

(Received February 11, 2015; Accepted May 1, 2015)