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Hemodynamic activity in the limbic system predicts reoffending in women

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ABSTRACT

Previous research (Aharoni et al., 2013, 2014) found that hemodynamic activity in the dorsal anterior cingulate cortex (dACC) during error monitoring predicted non-violent felony rearrest in men released from prison. This article reports an extension of the Aharoni et al. (2013, 2014) model in a sample of women released from state prison ($n = 248$). Replicating aspects of prior work, error monitoring activity in the dACC, as well as psychopathy scores and age at release, predicted non-violent felony rearrest in women. Sex differences in the directionality of dACC activity were observed—high error monitoring activity predicted rearrest in women, whereas prior work found low error monitoring activity predicted rearrest in men. As in prior analyses, the ability of the dACC to predict rearrest outcomes declines with more generalized outcomes (i.e., general felony). Implications for future research and clinical and forensic risk assessment are discussed.

1. Introduction

Rates of incarceration have been steadily increasing among women on a global scale (Harmon and Boppre, 2018; Reynolds, 2008). Indeed, the growth rate of the women's prison population in the U.S. is nearly double that of the male population in recent decades (Harmon and Boppre, 2018; Kelly, 2015; Reynolds, 2008). Despite increasing representation, limited systematic research has focused on incarcerated women. It is known that women who are incarcerated have increased rates of psychopathologies compared to incarcerated men and non-incarcerated women (Bronson & Berzofsky, 2017; Karlsson & Zielinski, 2020). Psychopathologies are often linked to alterations in brain-behavior relationships, many of which are relevant when considering antisociality. For instance, depression, Post-Traumatic Stress Disorder (PTSD), Borderline Personality Disorder (BPD), and Substance Use Disorder (SUD) diagnoses, are all elevated in women who are incarcerated, and these psychopathologies are subsequently related to heightened impulsivity (Bronson & Berzofsky, 2017; Jakubczyk et al., 2012; Karlsson & Zielinski, 2020; Kozak et al., 2019; Lawrence et al., 2010; Morris et al., 2020).

These psychopathologies are associated with abnormalities in the dorsal anterior cingulate cortex (dACC), a brain region associated with inhibition, error monitoring, and response selection (de Bruijn et al., 2006; Holroyd & Coles, 2002; Kiehl et al., 2000; Kosson et al., 2006; Malejko et al., 2021; Mathalon et al., 2003; van Rooij & Jovanovic, 2019; van Veen & Carter, 2002; Vega et al., 2015; Yang et al., 2021; Zilverstand et al., 2018). Prior studies have also linked individual differences in dACC activity with risk for criminal re-offending. Aharoni et al. (2013; 2014) reported that low activity in the dACC during error monitoring prospectively predicted non-violent felony rearrest in a sample of men released from prison.[1] This work reinforced previous research suggesting the importance of paralimbic dysfunction as a mediator between cognitive control and antisocial behavior (Kiehl, 2006). Though criminal behavior is the result of complex interactions of innumerable environmental, psychological, and biological factors, the extent to which sex may influence brain-behavior relationships concerning error monitoring and re-offending is an open question, as the relationship has only been assessed in males thus far (Aharoni et al., 2013; 2014).

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[1] In the U.S., a felony is commonly defined as a crime of high-seriousness than may be punishable by death or a year or more in prison. Felonies can be further broken down into non-violent felonies (e.g., major larceny/theft, fraud, and drug offenses) and violent felonies (e.g., murder, battery, and assault).

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Sex differences in error monitoring related brain activity have been demonstrated in multiple studies (Garavan et al., 2006; Liu et al., 2013; Weafer & de Wit, 2014; see Weafer, 2020 for a comprehensive review), all of which suggest a greater level of activation during response inhibition and error monitoring in women compared to men. Yet, the relevance of sex differences in the relationship between error monitoring activity and trait impulsivity is unclear, heightening the import of investigations concerning the influence of sex on relationships between error monitoring and impulsivity related outcomes.

While neurobiological measures appear to aid in the prediction of impulsive outcomes (Delfin et al., 2019; Kiehl et al., 2018; Pardini et al., 2014), this study marks the first attempt to conduct an out-of-sample extension of the Aharoni et al. (2014) error monitoring model in women—assessing potential sex differences in the relation of error monitoring and impulsive outcomes. As in previous studies, error monitoring activity was captured via a classic Go/NoGo task designed to test one's ability to inhibit prepotent motor responses—and was defined as the contrast between commission errors versus correct hits. Our predictions were that for felony rearrest and non-violent felony rearrest in women,[2] (1) the dACC will exert an incremental predictive effect above and beyond other established risk factors (e.g., age and psychopathic traits), and (2) a multivariate model that includes the dACC will predict better than models without the dACC.

2. Methods

2.1. Participants

Participants were 248 incarcerated women ranging in age from 21 to 58 y (M = 35.03, SD = 7.70). Approximately 10 % were left-hand–dominant. Based on National Institutes of Health racial classification, 82.7 % of the sample self-identified as white, 7.7 % as black/African American, 6.9 % as American Indian, and 1.6 % as mixed/other. Ethnically, 58.5 % identified as Hispanic, 38.7 % as Not Hispanic, and 2.8 % chose not to respond.

All 248 participants were determined to have no history of major traumatic brain injury (as defined by a loss of consciousness for longer than 24 h),[3]no lifetime history of a psychotic disorder, and had an estimated general IQ of greater than 65 (as estimated by the vocabulary and matrix reasoning subscales of the Wechsler Adult Intelligence Scale; see Ryan & Ward, 1999) (see Table 1 for additional demographic descriptives). Participants reported having normal hearing, and visual acuity was normal or corrected to normal with the use of contact lenses or magnetic resonance imaging (MRI) compatible glasses. Volunteer research participants were paid an hourly rate commensurate with standard pay for work assignments at their facility. Participants completed several psychological and behavioral assessment measures and an fMRI-based inhibition task using the Mind Research Network's Mobile MRI system before release from one of two New Mexico state correctional facilities. After being released, the participants in the sample were tracked from 2007 to 2019. Participants provided written informed consent in protocols approved by the institutional review board by the Independent Review (E&I) Services for the Mind Research Network.

Table 1
Participants demographic, PCL-R scores, and Substance Use Disorder Rates.

	Mean	*SD*	Min.	Max.	Overall sample endorsed (%)
Age (years)	35.0	7.7	21	58	
IQ	94.7	10.3	66	123	
PCL-R total scores	18.6	6.1	2.2	34.0	
Factor 1 scores	4.4	2.6	0	11.0	
Factor 2 scores	12.2	3.8	0	20.0	
Handedness (right)					90.0
Alcohol use disorder					72.1
Substance use disorder					95.1

Note: For alcohol and substance use disorder, input values are 1 = absent, 2 = history of abuse, and 3 = history of dependence. Percentage of sample endorsed represent those that have a history of abuse for alcohol, or at minimum one substance category (out of: sedatives, cannabis, stimulants, opioids, cocaine, and hallucinogens).

2.2. Covariate risk assessment

Data from additional risk factors (Hare's Psychopathy Checklist – Revised [PCL-R] and the participant's age at release) were obtained to examine the incremental predictive validity provided by the established ROI—the exact dACC error monitoring coordinates used in Aharoni et al. (2013; 2014)—thus providing an out-of-sample test of the model used in Aharoni et al. (2014) (Hare, 2003). These additional variables have been previously found to predict antisocial behavior in incarcerated populations (Aharoni et al., 2014; Olver & Wong, 2015). Scores from the Hare PCL-R—a semistructured interview and archival analysis which assesses psychopathy in incarcerated, forensic, psychiatric, and normal populations—were included as primary risk factors. These assessments were conducted by trained raters. 2.4 % of the sample (n = 248; M = 18.60; SD = 6.11) met the pre-established criteria for a diagnosis of psychopathy (score of ≥30). The PCL-R further splits into two separate clusters of traits: factor 1 includes interpersonal/affective traits (such as glibness and lack of empathy) and factor 2 includes antisocial behavioral traits (such as impulsivity and early behavioral problems). As in Aharoni et al. (2014), these factors and their interaction were entered individually into the overall predictive models, not including total PCL-R score (due to high collinearity).[4]

Additional exploratory correlational analyses were also conducted with the following variables (see Table S4): the participant's estimated IQ, their alcohol/drug dependency (as assessed from the Structured Clinical Interview for the DSM [SCID] via determinations of lifetime abuse or dependence [scoring: 1 = no lifetime abuse/dependence, 2 = lifetime abuse, and 3 = lifetime dependence]) (5th ed.; DSM–5; American Psychiatric Association, 2013),[5] their State-Trait Anxiety Inventory total summed score (STAI: Spielberger, 1983), the Barratt Impulsiveness Scale with three subscales measuring attentional impulsivity, motor impulsivity, and non-planning impulsivity (BIS-11; Patton et al., 1995), their self-reported education level, incarceration history (as coded from their PCL-R interview and institutional file review), and the presence of

[2] Violent felony rearrests within this sample were uncommon (n = 29), thus no analyses were conducted on violent outcomes due to low base rate. See supplementary materials for exploratory analyses concerning general rearrest (i.e., arrests of any severity).

[3] Six participants had a history of moderate TBI (as defined by a loss of consciousness longer than 30 min). Primary effects observed in the full sample (n = 248) were also observed in a sample excluding those with moderate TBI (n = 242).

[4] Consistent with Aharoni et al., 2013, we found no associations between Go/NoGo behavioral data and any types of rearrest in univariate nor multivariate models. Also consistent with Aharoni et al., 2014, we found models including behavioral task data increased Somer's D statistics, indicating the occurrence of overfitting being driven by the behavioral data specifically. Due to these reasons, and a priori model specification from Aharoni et al., 2014, we focus instead on the reduced predictive model.

[5] Scoring for drug abuse/dependence is computed via an averaging across abuse/dependence in the following individual drug classes: sedatives, cannabis, stimulants, opioids, cocaine, and hallucinogens.

traits associated with borderline personality disorder (BPD; as quantified by each participant's sum of scores [0–2] across nine BPD trait questions in the SCID-II).[6]

2.3. Follow-Up procedure

Rearrest data, including arrest date and offense type, were obtained from the New Mexico's Administrative Office of the Courts, which collects all state and county criminal records. Approximately 39.1 % of the sample was rearrested at least once for a felony between their release date (ranging from 2007 to 2017) and their follow-up date (August 2019). In line with previous predictive modeling, minor parole and probation violations were excluded from analysis, and the remaining offenses were further classified as violent or non-violent when warranted. Within our follow-up window (average time of 6 y and 9 mo), a larger portion of the sample was first rearrested for non-violent offenses (25.4 %) than for violent offenses (4.8 %).

2.4. Behavioral task

Behavioral impulsivity was measured during fMRI using the Go/NoGo task. The task, modeled after the work of Kiehl et al. (2000), presents participants with a frequently occurring target (the letter "X"; occurrence probability, 0.84) interleaved with a less-frequent distracter (the letter "K"; occurrence probability, 0.16) on a computer screen. Participants were instructed to depress a button with their right index finger as quickly and accurately as possible whenever they saw the target (the "go" stimulus) and not when they saw the distractor (the "no-go" stimulus). Because targets are more frequent than distracters in this task, a prepotent response toward the targets is elicited. When a distractor is presented, participants are required to inhibit their button response, which increases the rate of commission errors. Successful performance on this task requires the ability to monitor error-related conflicts and to selectively inhibit the prepotent go response on cue. Before their scan session, participants completed a brief practice session of ~10 trials.

2.5. Experimental design

The experimental design used on all participants was adopted from Kiehl et al. (2000) and is identical to that of Aharoni et al.'s (2013). Two scanning runs, each composed of 246 visual stimuli, were presented to participants using Presentation, a computer-controlled visual and auditory software (Neurobehavioral Systems). Stimuli were displayed on a rear-projection screen mounted at the rear entrance to the magnet bore. Each stimulus appeared for 250 ms in white text within a continuously displayed rectangular fixation box.

The stimulus onset asynchrony (SOA) between go stimuli varied pseudorandomly among 1,000, 2,000, and 3,000 ms, subject to the constraint that three go stimuli were presented within each consecutive 6-s period. The no-go stimuli were interspersed among the go stimuli in a pseudorandom manner subject to three constraints: the minimum SOA between a go and a no-go stimulus was 1,000 ms; the SOA between successive no-go stimuli was in the range of 10 ± 15 s; and no-go stimuli had an equal likelihood of occurring at 0, 500, or 1,000 ms after the beginning of a 1.5-s acquisition period. By jittering stimulus presentation relative to the acquisition time, the hemodynamic response to the stimuli of interest was sampled effectively at 500-ms intervals.

Behavioral responses were recorded by using an MRI-compatible fiberoptic response device—created by Lightwave Medical. Correct hits were defined as go (i.e., X-stimuli) events that were followed by a button press within 1,000 ms of stimulus onset. Correct rejections were defined by an absence of a motor response within 1,000 ms of the no-go stimulus. Commission errors were defined as the presence of a response within 1,000 ms of the onset of a no-go stimulus.

2.6. Image acquisition

MRI acquisition parameters were identical to those discussed in Aharoni et al. (2013) and will only briefly be described here. Images were collected with a mobile Siemens 1.5-T Avanto system with advanced SQ gradients (max slew rate, 200 T/m/s; 346 T/m/s vector summation, rise time 200 μs) equipped with a 12-element head coil. The echoplanar image gradient-echo pulse sequence (repetition/echo times, 2,000/39 ms; flip angle, 75°; field of view, 24 × 24 cm; 64 × 64 matrix; 3.4 × 3.4-mm in-plane resolution; 5-mm slice thickness; 30 slices) effectively covers the entire brain (150 mm) in 2,000 ms. Head motion was limited by using padding and restraint.

2.7. Preprocessing

Functional images were reconstructed offline at 16-bit resolution and manually reoriented to approximately the anterior commissure/posterior commissure plane. The functional images were despiked using ArtRepair and motion corrected using INRIAlign—a motion correction procedure unbiased by local signal change (Freire, Roche, & Mangin, 2002). Functional images were spatially normalized to the Montreal Neurological Institute template via EPInorm (an affine transform followed by a nonlinear registration of the *EPI* image to an *EPI* template in standard space) and spatially smoothed (12 mm full-width half maximum) in SPM12 (Calhoun et al., 2017). High frequency noise was removed by using a low-pass filter (cutoff, 128 s).

2.8. Individual and group level analysis

As in Aharoni et al. (2013), response types (correct hits and commission errors) were modeled as separate events. Event-related responses were modeled using a synthetic hemodynamic response function composed of two gamma functions. The first gamma function modeled the hemodynamic response using a peak latency of 6 s. A term proportional to the derivative of this gamma function was included to allow for small variations in peak latency. The second gamma function and associated derivative was used to model the small "overshoot" of the hemodynamic response on recovery. A latency variation amplitude-correction method was used to provide a more accurate estimate of the hemodynamic response for each condition that controlled for differences between slices in timing and variation across regions in the latency of the hemodynamic response (Calhoun et al., 2004).

Individual runs were modeled together at first level of analysis, and functional images were computed for each participant that represented hemodynamic responses associated with commission errors and correct hits, relying on a previously established set of coordinates to constrain the second level analysis within the present sample (Aharoni et al., 2013; Steele et al., 2014a). General linear models included regressors to model motion (six parameters).

2.9. Analytic strategy

The primary hypothesis—that the dACC will exert an incremental predictive effect above and beyond other established risk factors—was evaluated by using Cox proportional-hazards regression (Cox, 1972). A Cox regression is a semiparametric test that investigates the effect of variables of interest on the time it takes for an event to happen—in this case, rearrest—while also estimating time courses of those that have yet to reach that event (censored cases). The dependent variable is the proportion of cases surviving the event (the cumulative survival function). In order to interpret the effect of individual variables on the

[6] Note: Twenty participants were missing BPD data. Thus, supplementary correlational and regression analyses utilizing this variable have a sample size of $n = 228$.

cumulative survival function, hazard ratios (i.e., exp[B]) are computed. These hazard ratios characterize an individual's relative odds of reaching the event for every-one unit change in the risk factor (e.g., error monitoring brain activity), while controlling for other covariates. Additionally, supplementary analyses providing convergent support for Cox proportional-hazards regression results include binomial logistic regressions testing the univariate and multivariate relationship between the variables of interest and group membership (i.e., not rearrested vs rearrested, not rearrested for felony vs rearrested for felony, and not rearrested for non-violent felony vs rearrested for non-violent felony) across four different time periods (1, 2, 3, and 4 years) (see Table S3).

The secondary hypothesis—that a multivariate model that includes the dACC will predict better than models without the dACC—was evaluated by using receiver operating characteristic (ROC) curves which describe the differences between those who were and were not rearrested as a function of the predictors in the model (i.e., discrimination). While most assessments of ROC curves are time independent, our analyses of AUC characteristics are evaluated per model at a variety of time points (6, 12, 24, & 36 mo) by utilizing Heagerty and Zheng's time-dependent ROC curve function as found in the *risksetROC* package in *R*, version 3.60 (Heagerty and Zheng, 2005). This analysis yields an AUC per time point in order to evaluate each model's ability to discriminate those who were and were not re-arrested across a series of time scales.

3. Results

3.1. Group level neuroimaging analysis

Hemodynamic differences between commission errors and correct hits were extracted from an a priori 14 mm radius sphere (Aharoni et al., 2013; Steele et al., 2014a) centered around the seed coordinate in the ACC (x = -3, y = 24, z = 33: See Fig. 1a for seed coordinate and Fig. 1b for group level activation map) in the form of a mean β-values for each participant via the MarsBaRs plugin for SPM (Brett et al., 2002).[7] Additionally, a group level analysis of 32 ROIs was conducted to assess the reliability of error monitoring activation compared to previous literature (Steele et al., 2014a: see Table S1 for full replication of hemodynamic activity).

3.2. Survival analysis

A multivariate Cox proportional-hazards regression was used to examine the shared and unique influence of the dACC among other predefined risk factors (release age, PCL-R factor 1, PCL-R factor 2, and PCL-R factor interaction) on days to non-violent and general felony rearrest (see Table 2; see Table S2 for general rearrests; see Figure S1 for Kaplan-Meier curves for all rearrest outcomes). For multivariate analyses, predefined risk factors were entered into the regression in the first block, to assess whether the dACC exerted significant influence on the model after controlling for the other variables of interest.

3.2.1. Is Neurobiological Error Monitoring Information Associated with Non-Violent Rearrest in Women?

To test our primary hypothesis (that the dACC will exert an incremental effect above and beyond other established risk factors in the prediction of non-violent and general felony rearrest—see Table S2 for general rearrests), we tested the Aharoni et al. (2014) model—henceforth referred to as the error monitoring model—including previously defined risk factors: 1) the women's release age, PCL-R factor 1, PCL-R factor 2, their interaction, and the dACC's mean β-values for commission error versus correct hit trials in the sample of incarcerated women, $n = 248$.

For non-violent felony rearrest, a significant overall effect was obtained for the multivariate model ($p < 0.001$). As expected, a lower age at release and higher PCL-R factor 2 scores were each significantly associated with days to non-violent rearrest ($p = 0.001$). Also, as predicted, dACC activity exhibited a significant association with non-violent felony rearrest above and beyond these other risk factors, mirroring previous findings in male samples (Aharoni et al., 2013, 2014; Steele et al., 2015) (see Figure S2 for visualization of effect). For every-one unit increase in dACC activity, there was a 0.72 increase in the probability of rearrest for a non-violent crime ($p = 0.018$) (see Table 2 & Table S3).

For general felony rearrest, a significant overall effect ($p < 0.001$) was obtained for the multivariate model (see Table 2).[8] As expected, a lower age at release and higher PCL-R factor 2 scores were each significantly associated with days to felony rearrest ($p = 0.003$ and $p = 0.001$, respectively) (Eisenbarth, Osterheider, Nedopil, & Stadtland, 2012; Huebner, DeJong, & Cobbina, 2010). dACC activity exhibited a marginally significant association with felony rearrest above and beyond these other risk factors ($p = 0.088$) (see Table S3 for further convergent support and Figure S2 for visualization of effect).

3.2.2. Does the Inclusion of Neurobiological Error Monitoring Information Increase the Accuracy of Statistical Models in Predicting Non-Violent Rearrest in Women?

The receiver operating characteristic (ROC) curve is a direct way to test a model's accuracy—indicating the true positive (sensitivity) and false positive (1 - specificity) ratio of a model. An area under the curve (AUC) analysis was conducted to discriminate between those women rearrested and not rearrested as functions of the error monitoring model.

In order to test our secondary hypothesis (that a multivariate model of non-violent rearrest that includes the dACC will outperform one that doesn't), we fitted the multivariate model with and without dACC ROI data at a six-month time point.[9] As predicted, the multivariate model without dACC activity reports an AUC of 0.683, and an improved AUC of 0.701 when including the dACC factor. The accuracy of the model was found to be relatively stable over a span of six to thirty-six months (with values ranging from 0.700 to 0.701).

Overall, we find that predictions of non-violent felony rearrest are incrementally benefited from the inclusion of dACC activity.

4. Discussion

This study provides an out-of-sample extension of the Aharoni et al. (2014) error monitoring model using a large sample of women. Our results demonstrate modest improvement in the prediction of later rearrest for non-violent offenses in women, using a predefined index of functional brain activation in the dACC—a region previously implicated in error monitoring, inhibition, and impulsivity (Bastin et al., 2016; Kiehl et al., 2000; Orr & Hester, 2012; Spunt et al., 2012; Steele et al., 2014a). Likewise, our results uphold previous findings in the literature, underscoring the importance of age at release and antisocial/developmental lifestyle score (PCL-R Factor 2) for predicting subsequent rearrest in incarcerated women (Eisenbarth et al., 2012; Huebner et al., 2010).

Previous attempts to test neurobiologically informed risk models for rearrest have been limited by the use of relatively small samples (by actuarial standards) leaving them unable to test the out-of-sample utility

[7] Participants averaged 8.45 commission errors during the task. Three participants were identified as outliers based on their high rate of commission errors (as assessed by a value higher than 3rd quartile + (1.5 x interquartile range). Primary effects observed in the full sample ($n = 248$) were also observed in a sample excluding those identified as outliers ($n = 245$).

[8] Due to our primary interest in the full multivariate model, reported results focus on multivariate metrics.

[9] Due to the marginal effect of dACC activity on general felony rearrest reported in Table 2, we focus AUC analyses on non-violent felony rearrest.

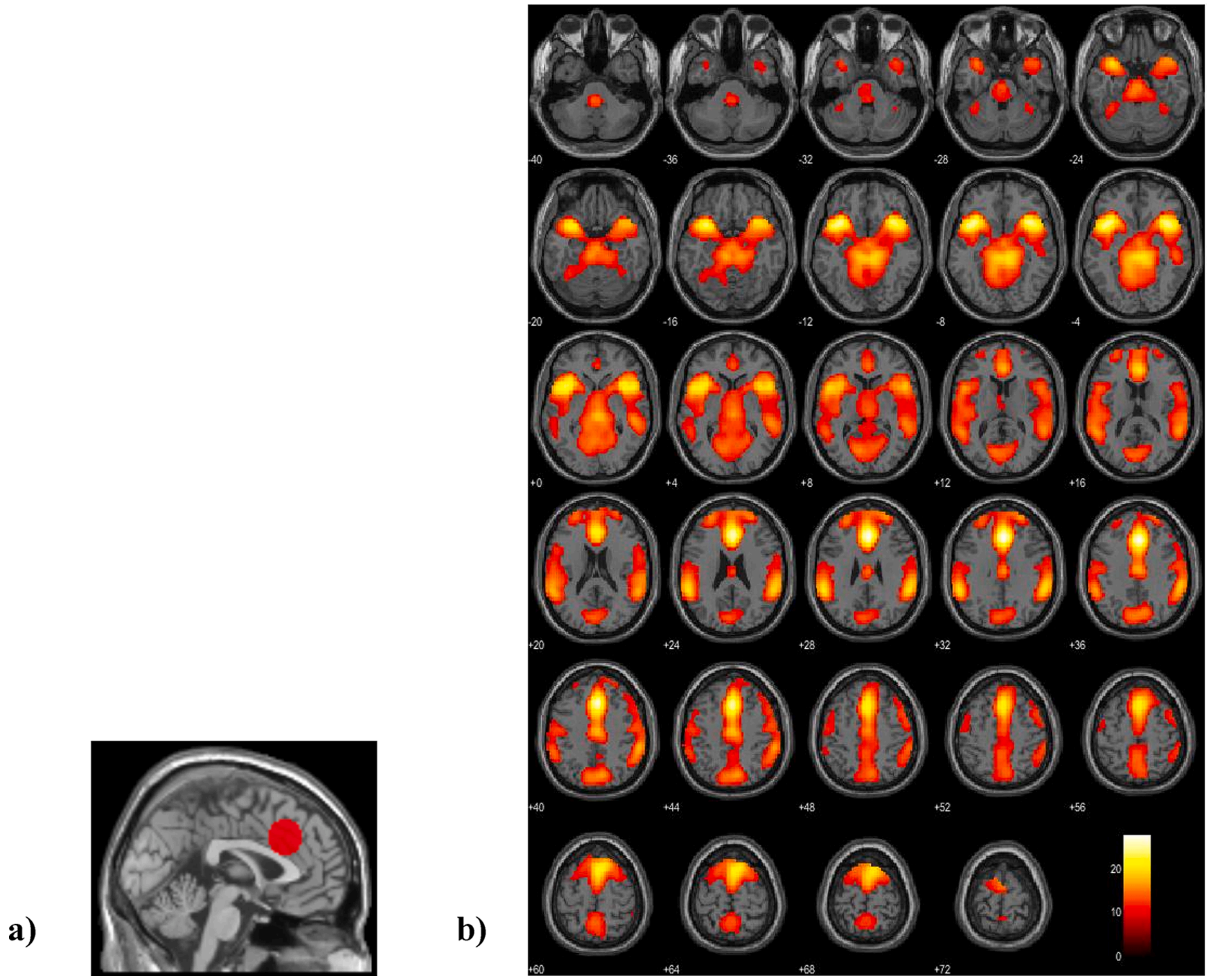

Fig. 1. a) A priori seed region (red) for hemodynamic response to commission errors vs correct hits in the dACC from a Go/NoGo task with an independent sample of 102 healthy adult nonoffenders; peak voxel x = − 3, y = 24, z = 33 (Steele et al., 2014a). b) Map of hemodynamic activity in sample of incarcerated women ($n = 248$) during commission errors vs correct hits from axial view. Peak activation was located at x = 3, y = 26, z = 34, within the dACC (threshold: $t > 10$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Effect of individual predictors on non-violent and general felony rearrest.

	Unadjusted Hazards			Adjusted Hazards		
Model/Predictor	*B (SE)*	*P value*	exp[B] (CI)	*B (SE)*	*P value*	exp[B] (CI)
Non-Violent Felony Rearrest (*n* = 248, 79 rearrests)						
- Age at release	−0.057 (0.016)	<0.001***	0.945 (0.915–0.975)	−0.052 (0.017)	0.002**	0.949 (0.918–0.981)
- PCL-R factor 1 score	0.025 (0.045)	0.570	0.975 (0.893–1.064)	0.077 (0.217)	0.721	1.081 (0.707–1.652)
- PCL-R factor 2 score	0.126 (0.033)	<0.001***	1.135 (1.064–1.210)	0.244 (0.070)	0.001**	1.251 (1.091–1.434)
- PCL-R factor interaction	0.002 (0.003)	0.517	1.002 (0.997–1.007)	−0.016 (0.015)	0.275	0.984 (0.955–1.013)
- dACC	0.310 (0.136)	0.023*	1.364 (1.045–1.781)	0.334 (0.141)	0.018*	1.396 (1.058–1.842)
Felony Rearrest (*n* = 248, 97 rearrests)						
- Age at release	−0.050 (0.014)	<0.001***	0.951 (0.925–0.978)	−0.044 (0.015)	0.003**	0.957 (0.930–0.986)
- PCL-R factor 1 score	−0.017 (0.040)	0.677	0.983 (0.909–1.064)	−0.012 (0.118)	0.949	0.988 (0.684–1.427)
- PCL-R factor 2 score	0.126 (0.029)	<0.001***	1.135 (1.071–1.202)	0.197 (0.060)	0.001**	1.218 (1.084–1.369)
- PCL-R factor interaction	0.002 (0.002)	0.324	1.002 (0.998–1.007)	−0.009 (0.013)	0.464	0.991 (0.966–1.016)
- dACC	0.216 (0.124)	0.082†	1.241 (0.973–1.582)	0.220 (0.129)	0.088†	1.246 (0.968–1.604)

Results of Cox regression analyses examining the predictive effect of the dACC on non-violent and general felony rearrest. Unadjusted hazard values reflect univariate analyses, and adjusted hazard values reflect multivariate analyses including all variables of interest. All variables are mean centered, and reported effects are two-tailed. Table reports unstandardized B and relative risk ratio (exp[B]). † $p < .10$, *$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$.

of the models more generally (Aharoni et al., 2013, 2014; Delfin et al., 2019; Steele et al., 2015). These same samples have been comprised of all (Aharoni et al., 2013 & Aharoni et al., 2014: $n = 96$; Zijlmans et al., 2021: $n = 127$) or mostly (Delfin et al., 2019: $n = 44$, 39 males) male subjects, leaving the generalizability of these models in women an open question.

The present study addressed these limitations by conducting a large ($n = 248$) out-of-sample test of the error monitoring model in an independent sample of women, for non-violent and general felony rearrest. To our knowledge, the present study is the first in the literature to demonstrate the value of impulsivity related neurobiological activity for the prediction of rearrest in women.

Overall, our results corroborate previous literature demonstrating that theoretically-relevant measurements of functional brain activity may improve accuracy of risk models designed to predict antisocial outcomes (Aharoni et al., 2013; Aharoni et al., 2014; Camchong et al., 2013; Delfin et al., 2019; Janes et al., 2010; Pardini et al., 2014; Paulus et al., 2005; Sinha & Li, 2007; Steele et al., 2014b; Steele et al., 2015). More specifically, our results directly replicate the previously demonstrated (Aharoni et al., 2013, 2014; Steele et al., 2015) utility of error monitoring activity in predicting non-violent felony rearrest above and beyond other variables of interest (i.e., age at release and PCL-R Factor 2). Additionally, as seen in previous literature (Aharoni et al., 2013, 2014; Zijlmans et al., 2021), more modest predictive effects of error monitoring activity on general felony rearrest were also replicated via cox hazard and binomial logistic regression analyses (see Table 2 and Table S3). These effects are noteworthy given the broad definition of our outcome measure (felony rearrest). On even broader rearrest offenses (i.e., general rearrest including arrest of any category) error monitoring activity had no predictive utility (see Table S2 and Table S3), suggesting a stronger relationship between error monitoring activity and specific outcomes (i.e., non-violent felony rearrest) compared to more general outcomes (i.e., general rearrest and general felony rearrest). Our results also reinforce previous research suggesting the importance of paralimbic dysfunction as a mediator between cognitive control and antisocial behavior (Kiehl, 2006), as well as sex differences in the relationship between these paralimbic substrates and behavioral outcomes (Liu et al., 2013).

While prior fMRI research has suggested that increased engagement of error monitoring is associated with decreased rates of non-violent rearrest in men (Aharoni et al., 2013; Aharoni et al., 2014; Steele et al., 2015), other analyses in young males have failed to replicate this effect (Zijlmans et al., 2021). One potential explanation for this null finding is that juveniles and younger adults exhibit decreased error monitoring activity and inhibitory control more generally compared to older adults (Jaeger, 2013). Considering the effects shown in adult men, our results suggest the inverse for women: *lower* error monitoring activity was associated with non-violent rearrest. Notably, previous research utilizing the same Go/NoGo task has demonstrated not only sex differences in limbic activations during error monitoring, with women largely showing greater activations during failed inhibitions (Garavan et al., 2006; Liu et al., 2013; Weafer & de Wit, 2014; Weafer, 2020), but also sex differences in the relationship between those activations and other impulsivity measures (Liu et al., 2013).

One potential explanation of the positive association between error monitoring activity and rearrest within this incarcerated female sample is that the error monitoring contrast of interest—false alarms vs correct hits during the Go/NoGo task—may also be capturing anxiety, stress related limbic activity, or even alternative inhibitory strategies (e.g., the inhibition of a prepotent response versus the suppression of an already-initiated response; Gärtner & Strobel, 2021). Compared to men, women are more likely to experience anxiety, and in turn, be diagnosed with an anxiety disorder within their lifetime (McLean et al., 2011). During neuroimaging, more specifically, women are more likely to experience anxiety inducing states, such as claustrophobia (Dewey et al., 2007), and task-induced stress has been demonstrated to engage limbic regions—such as the ACC—in women more than in men (Wang et al., 2007). However, a lack of association between dACC error monitoring activity and anxiety measurements within our sample (see Table S4) leave this explanation wanting. Future research is needed to test these questions, perhaps using different measures of anxiety alongside alternative inhibition tasks that are sensitive to differentiation of strategic approach.

Another potential explanation of the positive relationship between error monitoring activity and rearrest may be the increased prevalence of BPD traits within incarcerated women compared to samples of men (Black et al., 2007; Sansone & Sansone, 2011). While research suggests that error monitoring is preserved in individuals with BPD, aberrations in the neurophysiological activity giving rise to error monitoring processes have also been observed within BPD samples (Vega et al., 2015; Yang et al., 2021). Individuals with BPD show increased N2 amplitudes during the conflict monitoring state of error commission—an event-related response originating from the dACC and often suggested to relate to the Go/NoGo contrast used in the present work (Steele et al., 2015; Yang et al., 2021). Accordingly, there was a significant positive relationship between error monitoring activity and BPD traits within this sample (see Table S4). But supplemental analyses (see Table S5) suggest that BPD's covariance with error monitoring activity alone cannot account for the positive relationship to rearrest within our sample yet may still be contributing to the overall predictive utility of our error monitoring measure.

Sex differences in limbic regions are not limited to task-based activity nor their relation to task performance—additional research by Anderson and colleagues (2019) identifies the ACC as a sexually dimorphic region of the brain, with women having significantly larger ACC volumes than men. This line of research emphasizes that impulsive and antisocial behaviors in women need to be investigated independently from theories that have been established in male-dominant literatures (Anderson et al., 2019). Thus, more work is needed to understand sex-specific differences in the anatomical and activity profiles of limbic regions, as well as their relationships to impulsivity, BPD, and antisocial behavior (Greiner et al., 2015; Olson et al., 2016; Poels, 2007).

4.1. Limitations and future directions

Though our results provide support for the predictive utility of limbic activity in rearrest behavior, we caution against overinterpretation. Here, different measures of impulse control (PCL-R Factor 2 and dACC activity during errors) incrementally predicted re-arrest outcomes. However, criminal behavior is the result of a complex interaction of factors, including innumerable environmental and psychological variables (Aharoni et al., 2019; Allen & Aharoni, 2020). The observed incremental predictive utility of the dACC predicting rearrest highlights that multiple mechanisms subserve antisocial outcomes and capturing their complexity may benefit from a diversity of measurement modalities.

Caution is also warranted from a legal and ethical standpoint. Using evidence based-risk assessment techniques for "lower stake" decisions, such as treatment and early grant parole, has shown relative success in increasing treatment-program success and reducing antisocial behavior (Aos et al., 2006; Andrews, 2006; MacKenzie, 2006; Taxman, 2002). However, using risk assessment techniques against a criminal offender's interests is controversial (Starr, 2014). Whether the use of neurobiological information presents any unique concerns above and beyond traditional behavioral risk factors is the subject of a small but important body of literature (see Aharoni et al., 2022; Focquaert, 2019; Jurjako et al., 2019; Nadelhoffer et al., 2012). Ultimately, even if brain-based risk assessments demonstrably improve upon traditional risk assessment techniques, this does not necessarily mean that they ought to be utilized in legal decision making, nor would their implementation be straightforward process due to costs, complexity, and intrinsic variability in measure. Instead, the potential success of brain-based models for risk assessment should highlight the importance of continued discussion about the ethical and legal standards required for their various uses and the translational treatment value (Aharoni et al., 2022).

Outside of the legal domain, research regarding neurobiologically informed risk assessment serves a critical basic research function by providing a way of testing causal relationships between brain and behavior. These causal mechanisms could prove useful in identifying potential behavioral interventions that may be beneficial in curbing antisocial behavior. Indeed, previous research has suggested that technologies such as transcranial direct current stimulation (tDCS) can be utilized to reduce self-reported aggression and even aggressive criminal intentions (Molero-Chamizo et al., 2019; Choy et al., 2018; Sergiou et al., 2022). While these tDCS studies report encouraging results, clinical interventions such as these must meet high standards of reliability and validity, and often warrant caution from ethical and legal standpoints as well (Large and Nielssen, 2017).

The present study provides an important out-of-sample extension of previous research on the neuroprediction of rearrest in a large sample of incarcerated women (Aharoni et al., 2013, 2014; Steele et al., 2015). Still, much work remains to be done to determine whether the predictive utility of limbic activity for antisocial behavior will ever reach high enough standards to warrant the practical use of neurobiologically informed risk assessment technology. Though highly targeted null-hypothesis testing methodologies—such as those employed in this manuscript—are useful in testing specific theories regarding cognitive function, such approaches are necessarily limited in scope. Follow up research should consider the integration of alternative impulsivity/inhibition tasks, additional regions of interest (e.g., the ventromedial prefrontal cortex, a region commonly implicated in aggression; Sergiou et al., 2022), and technological improvements such as increased scanner strength. Furthermore, data-driven approaches, such as machine learning techniques (e.g., independent component analysis), should be considered in order to uncover other potential neurobiologically based metrics—alongside social and psychological measures—that may be helpful in the prediction of antisocial behavior, including, but not limited to machine learning guided sex-specific and crime-specific models in large cross-validated analyses of various impulsivity/inhibition tasks and non-task based measures (Poldrack, Huckins, & Varoquaux, 2020). Until then, hypothesis-based neuropredictive modeling remains a helpful tool for testing potential causal mechanisms thought to mediate antisocial tendencies (Allen & Aharoni, 2020).

CRediT authorship contribution statement

Corey H. Allen: Data curation, Methodology, Writing – original draft, Formal analysis, Writing – review & editing. **Eyal Aharoni:** Data curation, Methodology, Writing – review & editing. **Aparna R. Gullapalli:** Data curation, Writing – review & editing. **Bethany G. Edwards:** Data curation, Writing – review & editing. **Carla L. Harenski:** Data curation, Writing – review & editing. **Keith A. Harenski:** Data curation, Writing – review & editing. **Kent A. Kiehl:** Data curation, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Data Availability Statement

The data presented in this article are not readily available because of the potential for personal re-identification of participants in the present sensitive population (incarcerated adult women). Interested parties should contact the Corresponding Author, Dr. Kent Kiehl (kkiehl@mrn.org) for the data used in this report which may be shared under a data use agreement.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.nicl.2022.103238.

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