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Authors

Dashtestani, Hadis
Zaragoza, Rachel
Pirsiavash, Hamed
et al.

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Canonical correlation analysis of brain prefrontal activity measured by functional near infra-red spectroscopy (fNIRS) during a moral judgment task

Hadis Dashtestani[1,2], **Rachel Zaragoza**[1], **Hamed Pirsiavash**[2], **Kristine M. Knutson**[3], **Riley Kermanian**[1], **Joy Cui**[1], **J. Douglas Harrison Jr.**[1], **Milton Halem**[2], and **Amir Gandjbakhche**[1,*]

[1)]Section on Analytical and Functional Biophotonics, National Institute of Child Health and Human Development, National Institutes of Health, Bethesda, MD, USA

[2)]Department of Computer Science and Electrical Engineering, University of Maryland Baltimore County, Baltimore, MD, USA

[3)]Brain Neurology Unit, National Institute of Neurological Disorders and Stroke, National Institutes of Health, Bethesda, MD, USA

Abstract

Individuals differ in the extent to which they make decisions in different moral dilemmas. In this study, we investigated the relationship between functional brain activities during moral decision making and psychopathic personality traits in a healthy population. We measured the hemodynamic activities of the brain by functional near-infrared spectroscopy (fNIRS). FNIRS is an evolving non-invasive neuroimaging modality which is relatively inexpensive, patient friendly and robust to subject movement. Psychopathic traits were evaluated through a self-report questionnaire called the Psychopathic Personality Inventory Revised (PPI-R). We recorded functional brain activities of 30 healthy subjects while they performed a moral judgment (MJ) task. Regularized canonical correlation analysis (R-CCA) was applied to find the relationships between activation in different regions of prefrontal cortex (PFC) and the core psychopathic traits. Our results showed a significant canonical correlation between PFC activation and PPI-R content scale (PPI-R-CS). Specifically, coldheartedness and carefree non-planfulness were the only PPI-R-CS factors that were highly correlated with PFC activation during personal (emotionally salient) MJ, while Machiavellian egocentricity, rebellious nonconformity, coldheartedness, and carefree non-planfulness were the core traits that exhibited the same dynamics as PFC activation during impersonal (more logical) MJ. Furthermore, ventromedial prefrontal cortex (vmPFC) and left

[*]Corresponding author: gandjbaa@mail.nih.gov (A. Gandjbakhche), Building 49, Room 5A82, 49 Convent Drive, Bethesda, MD, 20814.

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Compliance with Ethical Standards
All participants gave written, informed consent prior to the experiment, and the experiment was performed in compliance with the Declaration of Helsinki and approved by the National Institute of Child Health and Human Development’s Institutional Review Board.

lateral PFC were the most positively correlated regions with PPI-R-CS traits during personal MJ, and the right vmPFC and right lateral PFC in impersonal MJ.

Keywords

Canonical correlation analysis; functional near-infrared spectroscopy; moral judgment; prefrontal cortex; decision making; psychopathic traits

1 Introduction

Understanding the neural basis of human decision making has been the subject of numerous studies since it has substantial impact on daily life activities and social norms. Several studies have attempted to determine the pattern of the brain function during decision making based on moral judgment (MJ) exercises (Greene, Sommerville et al. 2001, Greene, Nystrom et al. 2004, Han, Glover et al. 2014, Han, Chen et al. 2016, Dashtestani, Zaragoza et al. 2018). These exercises elicit both cognitive and emotional neural responses, the degree of which depends not only on the exercise presented, but also on innate differences in the subjects. Using MJ exercises, differences in psychopathic personality traits have been delineated (Blair 1995, Blair 2001, Moretto, Làdavas et al. 2010, Koenigs, Kruepke et al. 2011, Marsh, Finger et al. 2011). Taxometric studies have shown that psychopathic traits lie in a spectrum and illustrate different degrees of deviation from normality rather than a unitary construct (Edens, Marcus et al. 2006, Neumann and Hare 2008, Lilienfeld, Watts et al. 2015). As such, an increasing body of work has investigated the implications of psychopathic traits on everyday functioning in a typical population (Widom 1977, Blonigen, Carlson et al. 2003, Hall and Benning 2006). However, the relationship between psychopathic traits and the neural basis of real-life decision making has not been fully explored, and many questions remain.

Almost all the studies that have attempted to determine the relationship between neuroimaging and psychopathic traits have used fMRI as the primary modality. However, this modality is expensive and often ill-suited for some patients and cognitive paradigms. Some patients with psychiatric conditions are difficult to assess in fMRI. These include patients with Alzhiemer’s, Parkinson’s, TBI, anxiety, schizophrenia, and mood disorders (Irani, Platek et al. 2007). Functional near-infrared spectroscopy (fNIRS) is a highly promising neuroimaging technique that provides an easy and patient friendly way to assess hemodynamic information on oxyhemoglobin (HbO) and deoxyhemoglobin (HbR) during cognitive tasks (Yuan 2013, Chowdhry, Gropman et al. 2018). fNIRS has acceptable spatial resolution, relatively high temporal resolution, and low susceptibility to head movements. As use of fNIRS has become common only recently, few studies have used it to analyze the neural basis of MJ in association with psychopathic traits.

In this paper, we examined the relationship between prefrontal brain activation measured by fNIRS and psychopathic traits in a normal adult population when they performed the same MJ task as in Greene et al. (2001). To assess individuals’ psychopathic traits, we used a self-report test, Psychopathic Personality Inventory Revised (PPI-R), which was developed by (Lilienfeld and Andrews 1996, Lilienfeld, Widows et al. 2005). This test was designed to examine personality features consistent with psychopathy in a healthy population. We applied canonical correlation analysis (CCA) (Hardoon, Szedmak et al. 2004) to find the relation between prefrontal activation captured through fNIRS and these psychopathic traits. Since the fNIRS and PPI-R data sets contain multiple measures from multiple subjects, finding the relation between them requires multivariate methods. Accordingly, we found the PPI-R core traits whose decomposition had the highest covariation with brain functional activity over four prefrontal regions, left and right lateral PFC, and left and right ventromedial PFC (vmPFC), during the MJ task.

This study, to our knowledge, is the first to determine the psychopathic core traits most correlated with brain functional activation in personal (emotionally salient) and impersonal (more logical than emotional) MJ decision-making. More recently, there have been some efforts investigating the ties between neural basis of MJ (in different contexts) and psychopathic traits. (Bjork, Chen et al. 2012), used fMRI to study changes in mesolimbic brain activities according to psychopathic traits measured by PPI-R scores, while (Glenn, Han et al. 2017) explored the neural basis of deception and its association with psychopathic traits in individuals. However, our approach sought to fill the gap between psychopathic traits and neuroimaging data during moral decision making using fNIRS.

Since there are contradictory results in assessment of psychopathic traits in healthy populations (Crowe and Blair 2008, Koenigs, Baskin-Sommers et al. 2011), neuroimaging techniques such as fNIRS can be as useful as traditional fMRI in exploring psychopathic traits. FNIRS provides a physiological explanation of aspects of psychopathic traits measured via PPI-R scores and their correlations with brain activities in different moral and emotional situations.

2 Materials and methods

2.1 NIRS data acquisition

FNIRS captures and records hemodynamic response of the brain using near infra-red light (700–1000 nm). We used an fNIRS Model 1000 (fNIRS Devices LLC, Potomac, MD, USA). This system has four sources and ten detectors, with a source-detector separation of 2.5 cm, for a total of 16 channels of oxyhemoglobin (HbO) and deoxyhemoglobin (HbR) detection. The sampling frequency was 2 Hz. The channel arrangement can be seen in Fig. 1. We assigned channels 1, 2, 3 and 4 to left lateral PFC, channels 5, 6, 7, 8 to the left vmPFC , channels 9, 10, 11, 12 to right vmPFC and channels 13, 14, 15 and 16 to right lateral PFC (McKendrick, Ayaz et al. 2014, Dashtestani, Zaragoza et al. 2018). The headband was always placed by one of two trained experimenters, who aligned the center between optodes 8 and 10, with nasion.

2.2 PPI-R-FS and PPI-R-CS data

Participants filled out PPI-R self-report questionnaires. PPI-R scores consist of two main categories, factor scores and content scales. The PPI-R factor score (PPI-R-FS) includes three main core traits: self-centered impulsivity, fearless dominance and coldheartedness. The PPI-R content scale (PPI-R-CS) has ten core traits: Machiavellian egocentricity, rebellious nonconformity, blame externalization, carefree non-planfulness, social influence, fearlessness, stress immunity, and coldheartedness. Two validity factors, virtuous responding and deviant responding, were obtained to detect participants who gave random, inconsistent or insincere answers. Subjects with poor validity scores were eliminated from our study. However, we included these two validity factors in our analysis to determine if there is any relationship between them and functional brain activity. It is worth noting that consideration of these two factors did not affect our analysis of the relationship between other psychopathic core traits with brain functional activity.

The population mean of total PPI-R scores is 50 with a standard deviation of 10 (Lilienfeld, Widows et al. 2005). Higher PPI-R scores indicate possession of greater than average levels of psychopathic traits. Traditionally, PPI-R scores equal to or above 65 are considered clinically significant in the field of psychopathy (Lilienfeld, Widows et al. 2005). We carefully considered the validity factors of PPI-R, and specifically controlled for “faking bad” replies, inconsistent responding, as well as virtuous responding. For these subcategories, T scores around 50 were considered valid responses. High Scores (T > 65) suggested that subjects perceived themselves positively and suggested potential deliberate attempts at positive impression management or "faking good" (Lilienfeld, Widows et al. 2005, Association 2013). Therefore, the one subject with a score higher than 65 was eliminated from this study.

Two other scores controlling for Inconsistent Responses (IR) were IR15 and IR40. For IR15, scores higher than 17 should be considered inconsistent and invalid. For instance, a score of 17 which occurs in less than 5% of a normative sample, indicated an atypical response and should raise questions concerning the validity of the full PPI-R (Lilienfeld, Widows et al. 2005, Association 2013). However, IR40 can be used as a determinative factor for the inclusion criteria since it has higher internal consistency and is more accurate. All the scores were T scores normalized based on age and gender (Lilienfeld, Widows et al. 2005, Association 2013).

2.3 Experiment design

We modeled our experiment after (Greene, Nystrom et al. 2004). The task consisted of personal and impersonal scenarios. Personal MJ tasks entailed emotionally salient scenarios, while impersonal tasks entailed more cognitive scenarios. We adopted 21 personal and 14 impersonal scenarios from their studies and added 5 non-moral and 5 random questions to control for random responses and fatigue. The order of the questions was pseudo-random. The task was developed using the E-Prime 2.0 software (Psychology Software Tools, Pittsburgh, PA). Each MJ question consisted of three slides: the first two slides described a scenario and the third slide presented a potential course of action. Participants then answered “Yes” or “No” by pressing “1” or “2” on the keyboard, respectively, with “Yes” indicating they agreed with the action presented. The subject had 30 s to make a decision, followed by a 15 s rest period. Figure 2 shows a diagram of the outline of the task (see Dashtestani, Zaragova, et al., 2018 for additional information on the designed tasks).

2.4 Participants

Data from 37 healthy subjects (22 female, 15 male) between the ages of 18 to 58 years (mean=33.7, SD=12.22) with no history of concussion or psychological and neurological disorders was obtained. The study was advertised by fliers distributed at different places, such as the National Institute of Health campus, metro stations, etc. Subjects were also enrolled through National Institute of Child Health and Human Development's Institutional recruitment process. The mean total PPI-R score was 49.69 with SD of 9.80, which suggested our subjects possessed normal levels of psychopathic traits. See Table 1 and 2 for other subscale measures. We discarded the data from seven subjects due to technical issues and invalid PPI-R scores.

2.5 Preprocessing and artifact removal

All preprocessing was done in MATLAB 2016a. We used the Modified Beer Lambert Law (MBLL) (Hiraoka, Firbank et al. 1993) to obtain the hemodynamic changes for each of the 16 channels. To attenuate the effects of heart beat, respiration and other high frequency noises, we used a low pass filter with 0.1 Hz cutoff frequency (Cooper, Selb et al. 2012, Anderson, Parsa et al. 2018). A moving average filter with a length of 1.5 ms was then applied on the fNIRS data to smooth the signal. In the last step of data preprocessing, we subtracted a fitted low order of 6 polynomial from the fNIRS data to remove linear and non-linear trends (Karamzadeh, Amyot et al. 2016).

The fNIRS segments were extracted according to the experiment design. Next, we took the average of the HbO/ HbR fNIRS time series across each channel over personal and impersonal trials, across subjects. The result was matrix $X \in \mathbb{R}^{30 \times 16}$, where 30 is the number of patients and 16 is the number of channels (spatial information) of fNIRS data. Although it is more accurate to use brain hemodynamic changes over time, i.e. HbO timeseries, using changes over time will give us the instantaneous relationship between hemodynamic response of the brain and psychopathic traits. Usually in correlation calculation, overall correlation is of interest, and the instantaneous relationship would not help us to draw any conclusions. Thus, we were interested in identifying the relationship between brain overall activities during personal/impersonal MJ decision-making and psychopathic traits measured by PPI-R. We used HbO/ HbR grand average in our analysis, accordingly.

2.6 Canonical correlation analysis (CCA)

In order to explore the relationship between two sets of multi-dimensional variables, the coordinate system in which the variables are described is crucial. Even a strong correlation between two sets of variables may not be visible if an inappropriate coordinate system is used (Hardoon, Szedmak et al. 2004). CCA, a method for assessing multivariate analysis of correlation, is useful in this regard. This technique draws relations between two sets when the sample size is relatively small in relation to the number of features, or when the two sets exhibit non-linear relations (Uurtio, Monteiro et al. 2017). It finds the coordinate system (basis vectors) in which the projections of each set onto these coordinates are maximized

(Hardoon, Szedmak et al. 2004, Thompson 2005). Figure 3 sketches an overview of CCA that can also be illustrated using the following notations.

Let X and Y be two multi-dimensional sets, $X \in \mathbb{R}^{n \times p}$ and $Y \in \mathbb{R}^{n \times q}$. It is worth noting that both sets should have the same number of rows, i.e. the same number of subjects.

The projections should satisfy the following properties (Morency and Baltrušpaitis 2017):

- There is a maximum correlation between the two linear projections:
  - $$(U, V) = \underset{u, v}{argmaxcorr}(H_x, H_y) = \underset{u, v}{argmaxcorr}(U^T X, V^T Y) \approx U^T \sum_{XY} V$$

    where U and V are the projection vectors:

    $$\begin{cases} U = [u_1, u_2, \ldots u_d] \\ V = [v_1, v_2, \ldots v_d] \end{cases}$$

    and d is the minimum rank of matrices X and Y.

- U and V should be orthogonal, or canonical, to each other:
  - $$u_i^T \sum_{XY} v_j = u_j^T \sum_{XY} v_i = 0. \qquad \text{for } ?? \neq j$$

- The projections have the unit variance:
  - $$\begin{cases} U^T \sum_{XY} U = I \\ V^T \sum_{XY} V = I. \end{cases}$$

Therefore, the kth pair of canonical variates is given by (Uurtio, Monteiro et al. 2017):

$$U_k = u_k^T \sum_X^{-1/2} X, and\ V_k = v_k^T \sum_Y^{-1/2} Y$$

where, u_k is the kth eigenvector of $\sum_X^{-1/2} \sum_{XY} \sum_Y^{-1} \sum_{YX} \sum_X^{-1/2}$.

The kth canonical correlation can be obtained by:

$$corr(U_x, V_y) = \rho_k$$

where ρ_k^2 is the kth eigenvalue of $\sum_X^{-1/2} \sum_{XY} \sum_Y^{-1} \sum_{YX} \sum_X^{-1/2}$. Since the first eigenvector accounts for much of the observed covariance in datasets of X and Y, the first pair of canonical variates represents this direction. Here we considered only the first pair of canonical variates for further analysis.

Often in brain imaging data, the number of features is greater than the total number of samples, as in our case. Overfitting of the training set could occur if not enough samples are used to train the CCA model. This would produce results that cannot be well generalized. Additionally, having too many features may exacerbate the problem since the features can be picked up and learned by the model. Thus, noise and inaccurate data may be introduced into the model in its learning process. Consequently, feeding a new sample to the model would lead to inaccurate predictions (Nasrabadi 2007). It is important to note that having a small training error and a huge test error simultaneously is an indicator of overfitting. In order to avoid this problem, we used regularized CCA (R-CCA). The regularization parameter, λ, keeps the parameters of the model small so that it is less likely to face the high bias problem (Kakade and Foster 2007). We chose a λ at which the model is stable and most of the variance is maintained.

To estimate the robustness of our R-CCA model, we used the leave-one-out cross validation (LOOCV) method and calculated the mean squared error (MSE). We specifically chose the LOOCV method since our sample size (n=30) was relatively small (Correa, Li et al. 2008). In this process, we trained the model without considering one sample. Using the trained model, we calculated the squared error for the left-out sample.

2.7 Data reconstruction

Since we found high canonical correlation between fNIRS and PPI-R-CS, we reconstructed functional brain activities in accordance with psychopathic traits, PPI-R-CS scores. As mentioned earlier, fNIRS data, including the spatial information, is composed of linear mixture of spatial components and their associated mixing vectors. For PPI-R scores, the data matrix is a mixture of PPI-R subcategories, corresponding to various measurements of psychopathic traits as well as their mixing vectors:

$$X = UC_x, Y = VC_y$$

where $U \in \mathbb{R}^{n \times d}$ and $V \in \mathbb{R}^{n \times d}$ are the first pair of canonical variates, respectively. d is the min[rank(X), rank(Y)] and since the two matrices of X and Y are fully ranked, d = min(16,4) = 4, min (16,10) = 10. C is the set of components matrices, $C_x \in \mathbb{R}^{d \times p}$, $C_y \in \mathbb{R}^{d \times q}$, which can be obtained by the least square approximation (Correa, Adali et al. 2010):

$$\hat{C}_x \approx (U^T U)^{-1} U^T X, \hat{C}_y \approx (V^T V)^{-1} U^T Y.$$

$\hat{C}_x$ indicates functional activities in PFC considering their correlation with PPI-R scores. Furthermore, $\hat{C}_y$ identifies the PPI-R subcategories that have stronger correlation with brain functional activities. In this manner, we obtain the cross covariation between neuroimaging (fNIRS) and behavioral (PPI-R) data.

3 Results

The canonical correlation analysis between HbO/HbR fNIRS data and PPI-R-FS revealed no significant correlations for personal or impersonal MJ. Moreover, running CCA on HbR and PPI-R-CS resulted in a non-significant correlation (p-value > 0.05). However, results of the canonical correlation between HbO data and PPI-R-CS were significant for both personal and impersonal MJ, indicating that there was at least one pair of non-zero correlations between the two sets. Accordingly, we focused on the results from CCA analysis of HbO and PPI-R-CS. The R-CCA algorithm was applied to the fNIRS data ($X \in \mathbb{R}^{30 \times 16}$) and the PPI-R-CS ($Y \in \mathbb{R}^{30 \times 10}$) to obtain the canonical correlation as well as canonical variates (U, V).

In order to tune the model via regularization parameter λ, we estimated the MSE for each model with different values of λ. Then we chose λ such that it minimized the MSE without overfitting the model. Figure 4 shows the MSE associated with different values of λ for both personal vs PPI-R-CS, and impersonal vs PPI-R-CS models. Based on Fig. 4, the MSE was smallest when λ is 0.01 and 0.03 for personal and impersonal models, respectively. However, these values tended to overfit the models. Our training error was small, but using LOOVC, we obtained a relatively large test error. This indicated that though the model fit the training data well, it was not generalized enough to make an accurate prediction for a new sample. Therefore, λ = 0.02 was chosen (for both models) since at this λ, the models did not overfit and still had reasonable mean error (Fig. 4).

To estimate the robustness of the R-CCA model, we used LOOCV, and found the MSE for personal and impersonal models to be 0.2921 and 0.1944, respectively. Figure 5 depicts the estimated MSE for each left out point (total of 30) in personal and impersonal models.

The highest correlations corresponding to the first component pair (U, V) between personal and impersonal neuroimaging and behavioral data were 70.81% and 73.24%, respectively. To obtain the personal and impersonal fNIRS component activity maps for each prefrontal region, we considered only the first set of reconstructed brain activities, $\hat{C}_x$, associated with the highest correlation. We called these reconstructed brain activities “brain functional activities” to distinguish between brain functional activation and avoid any confusion. Specifically, the brain functional activity map shows which areas of PFC exhibit similar dynamics to the PPI-R-CS core traits. Figure 6 (A, B) shows the personal/impersonal fNIRS component map for the prefrontal regions in conjunction with their corresponding head plots, parts C and D. Based on the personal fNIRS component activity map, left lateral PFC (channels 1, 2, and 3), along with left ventromedial PFC (vmPFC, channels 6, 7, 8, and 9), exhibited higher brain functional activities than other prefrontal regions. For the impersonal fNIRS component activity map, brain functional activities were much lower and limited to the right lateral PFC (channels 14 and 16) and a small area in the right vmPFC (channel 10).

From the second reconstructed matrix, $\hat{C}_y$, we found PPI-R-CS core traits that had stronger or weaker correlation with prefrontal activities during personal and impersonal dilemmas. We emphasize that these values are not correlation coefficients; rather, they reflect the proportion of components in each PPI-R-CS subcategory that have higher or lower covariation with fNIRS components. The PPI-R-FS psychopathic core trait, coldheartedness, contributed significantly to the personal MJ task brain activity, as did the PPI-R-CS psychopathic core trait, carefree non-planfulness. In contrast, Machiavellian egocentricity had relatively strong negative covariation with fNIRS components of brain hemodynamic response during the personal MJ task. See Table 3.

Impersonal MJ brain functional activity showed different PPI-R-CS ties. Machiavellian egocentricity, rebellious nonconformity and carefree non-planfulness contributed the most to fNIRS impersonal brain activities. All three showed positive covariation with the hemodynamic response of the brain. There were no significant negative covariations.

4 Discussion

Our approach enabled us to explore the linear and non-linear correlations between various factors of psychopathic traits and the hemodynamic response to cognitive tasks using fNIRS data and PPI-R scores. We considered the average HbO across fNIRS channels as the first feature set and three/ten subcategories of PPI-R-FS/PPI-R-CS as the second. Applying R-CCA on the HbO/HbR fNIRS data and PPI-R-FS resulted in non-significant canonical correlation. There was a significant canonical correlation between mean HbO over PFC regions and PPI-R-CS. Detecting non-significant canonical correlation between HbR and psychopathic traits could be due to the low signal-to-noise ratio of HbR than HbO (Strangman, Culver et al. 2002). R-CCA determines the components that have the greatest contribution to the strongest relationship between the two sets. Using the main (first) component, we reconstructed the brain hemodynamic responses. As can be seen in Fig. 6 (A), personal dilemma brain functional activities over the left lateral PFC and vmPFC were greater compared to other prefrontal areas, indicating brain activities in those PFC regions and PPI-R-CS undergo similar dynamics during personal dilemmas. (Greene, Nystrom et al. 2004, Greene 2007, Glenn, Raine et al. 2009) reported that vmPFC plays a critical role in personal, emotionally salient, MJ. In addition, several studies have reported that the dlPFC is also involved in MJ (Glenn, Raine et al. 2009, Han, Chen et al. 2015, Han, Chen et al. 2016, Dashtestani, Zaragoza et al. 2018). A meta-analysis conducted by Han (2017) reviewed 45 experiments with 959 subjects and identified similar areas of activation during MJ tasks (Han 2017). These regions are also engaged in working memory, direct attention maintenance, emotion regulations and switching between alternative choices in decision-making (Aron, Durston et al. 2007, Rossi, Pessoa et al. 2009, Lisofsky, Kazzer et al. 2014), (Sylvester, Wager et al. 2003, Boorman, Behrens et al. 2009). More importantly, (Glenn, Han et al. 2017) reported that dlPFC and vmPFC were associated with psychopathic traits in individuals when lying, while we detected significant activities in the same regions during MJ personal/impersonal decision-making. Thus, our results are in line with previous studies, which show that these PFC regions play a critical role in personal decision making even after the effects of the psychopathic traits are taken into account. It is worth mentioning that, in the impersonal dilemmas, PPI-R-CS traits and the changes in functional brain activity had weaker covariation compared to that of personal dilemmas. This seems logical, since impersonal MJ provokes emotions in subjects, but not as much as personal ones; thus, the vmPFC had less activation in impersonal compared to personal MJ scenarios.

We found the greatest covariation was between coldheartedness and personal MJ brain functional activities (Table 3). Carefree non-planfulness was another effective core trait in personal brain functional activity. These two traits have the most significant impact on functional brain activities according to our results. Many studies have pointed to coldheartedness as an isolated dimension in measuring psychopathic traits using behavioral assessments (Benning, Patrick et al. 2005, Berg, Hecht et al. 2015). Coldheartedness has also been theoretically recognized as a significant factor in psychopathy (Cleckley 1955, Lilienfeld and Andrews 1996). Moreover, Benning et al. (2003) via factor analysis (using principal axis factoring with Varimax Rotation) found that carefree non-planfulness produced a similar pattern to that of coldheartedness (Lilienfeld, Widows et al. 2005, Smith, Edens et al. 2011). Thus, our findings are in agreement with most of the literature, which considers these two traits separate factors in psychopathic trait analysis.

While Benning et al. (2003) loaded Stress Immunity, Social Potency (Influence), and Fearlessness in their first PPI factor (in a two-factor model), we did not find Social Potency (CCA_personal = 0.0653, CCA_impersonal = −0.0584) to be as strongly correlated as Stress Immunity and Fearlessness with hemodynamic response (Benning, Patrick et al. 2003, Neumann, Malterer et al. 2008). Fearlessness and Stress Immunity showed relatively mild correlations in personal fNIRS, but this did not hold true for impersonal fNIRS.

In contrast, Machiavellian egocentricity and rebellious nonconformity were the two psychopathic traits that had the maximum covariation with impersonal functional brain activity. These findings are consistent with studies that investigated PPI-R core traits through factor analysis using behavioral data (Benning, Patrick et al. 2005, Neumann, Malterer et al. 2008). Thus, during impersonal MJ, which elicits more reason, brain activation is highly correlated with Machiavellian egocentricity and rebellious nonconformity. It is interesting that Machiavellian egocentricity exhibits relatively high negative covariations with the main components of the fNIRS brain hemodynamic response in personal situations, versus high positive covariations during impersonal dilemmas. This shows psychopathic core traits may be differentially correlated with personal/impersonal hemodynamic brain activities.

In addition to the high correlations we found for carefree non-planfulness and coldheartedness with brain prefrontal activities during personal MJ, we also found they had strong ties with brain prefrontal activities during impersonal MJ. Benning's factor analysis found that these two traits together comprised factor C. All of these psychopathic traits have been recognized as the most prominent factors in factor analytic studies (Benning, Patrick et al. 2005, Neumann, Malterer et al. 2008, Blair 2013). Although our results were mostly in line with factor analysis studies, we found that the loadings for some variables were high, while the canonical weights of the respective variables were around zero. These findings may seem contradictory, but it should be noted that canonical weights pertain to the unique contribution of each variable, whereas factor loading represents overall correlations of the factors and the variables. In contrast to previous studies that used factor analysis in conjunction with behavioral datasets to determine and construct a unified tool for quantifying psychopathic traits (Benning, Patrick et al. 2003, Benning, Patrick et al. 2005, Neumann, Malterer et al. 2008), our study examined the relationship between quantified measurements of psychopathy (core traits) with brain functional activities during personal/impersonal MJ decision-making.

In summary, by extracting the relationship between functional activities over different brain regions and PPI-R-CS core traits, we found that left dlPFC and vmPFC brain activities were highly correlated with coldheartedness and carefree non-planfulness in personal MJ. In addition, individuals with higher Machiavellian egocentricity and rebellious nonconformity traits experienced more functional activities over right lateral PFC and a small area of vmPFC during MJ using impersonal dilemmas. These results show that determining the relationship between behavioral metrics and neural activities can help establish more accurate models since this approach not only considers subjects' actions, but also the physiological changes related to those actions.

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Highlights

- Relationship of prefrontal activity in moral judgment (MJ) and psychopathic traits
- Functional near infrared spectroscopy was used as neuroimaging modality
- Psychopathic traits measured by Psychopathic Personality Inventory Revised (PPIR)
- Highly correlated factors in personal MJ: coldheartedness, carefree non-planfulness
- In impersonal MJ: Machiavellian egocentricity, rebellious nonconformity
- Brain activity of personal MJ in vmPFC, left lateral PFC highly correlate with PPIR
- In impersonal MJ: right vmPFC, right lateral PFC highly correlate with PPIR

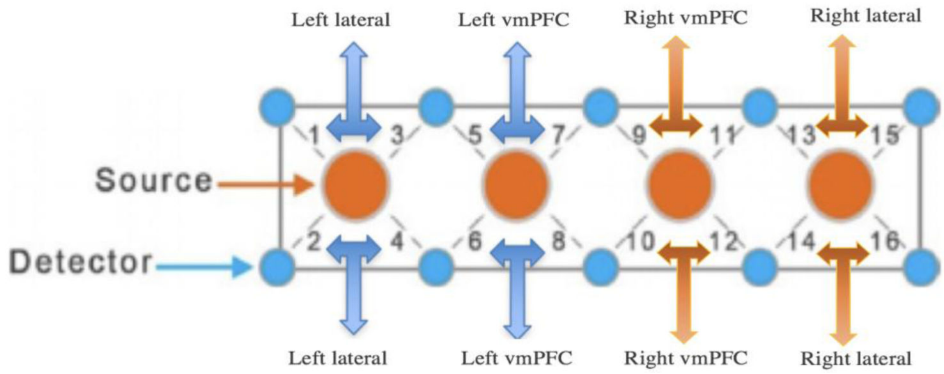

Figure 1.
The configuration of probes for the fNIRS device. There are 4 sources and 10 detectors resulting in 16 source/detector (channels) pairs.

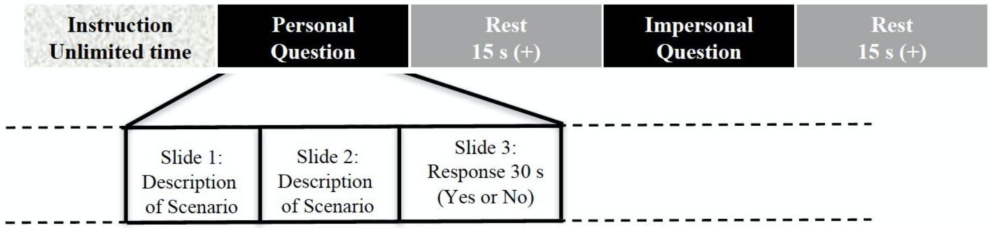

Figure 2.

Outline of the MJ paradigm for this study. Each question consisted of three slides with the first two slides describing a scenario, and the third presenting a course of action for which the participant indicated their agreement or disagreement.

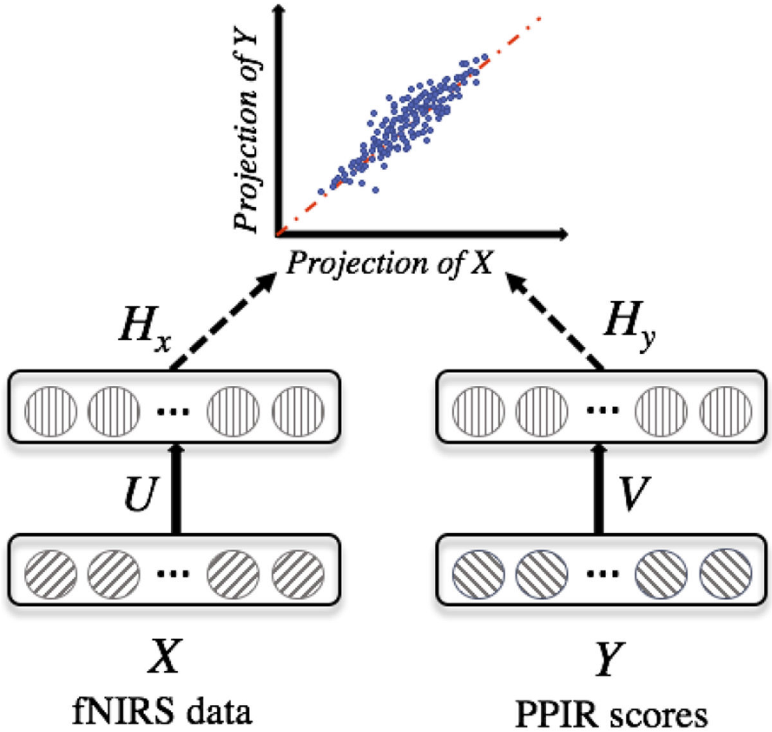

Figure 3.
Schematic overview of CCA. X and Y are the two multivariate sets with the same number of observations (Morency and Baltrušaitis 2017) .

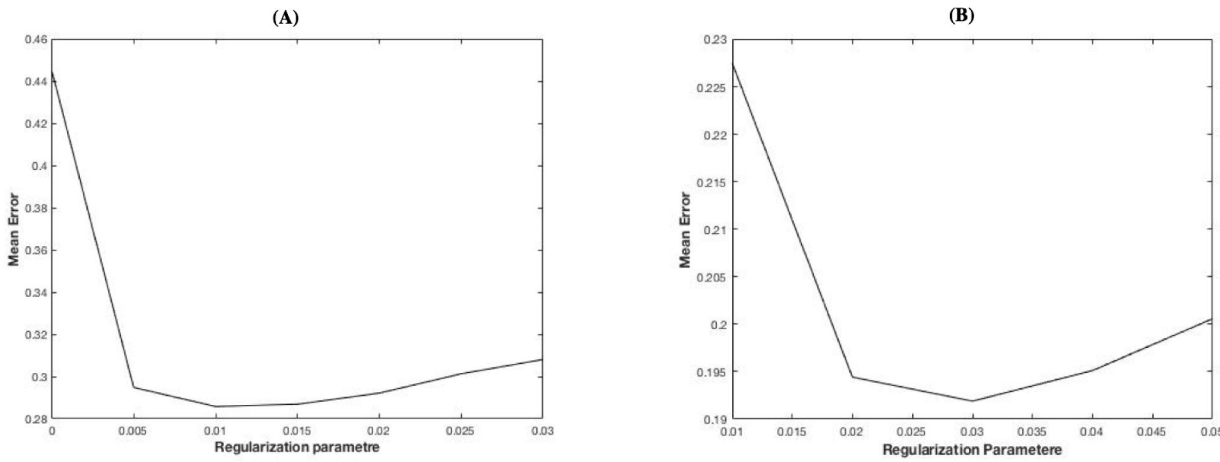

Figure 4.

Mean squared error (MSE) vs regularization parameter, λ, for personal (A) and impersonal (B) fNIRS data model. It can be seen that MSE is minimum when $\lambda = 0.01$ and 0.03 for personal and impersonal models, respectively.

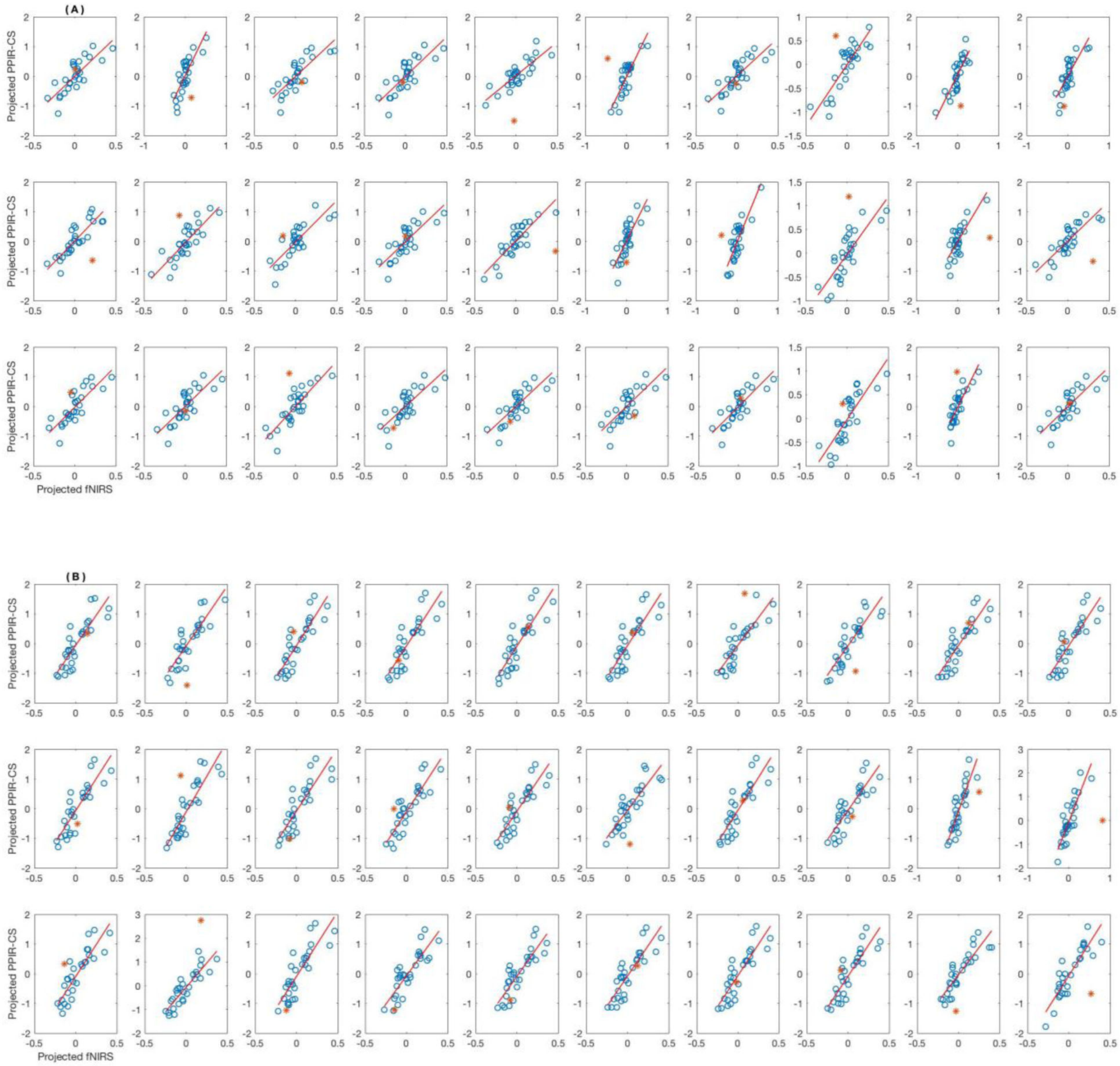

Figure 5.
The LOOCV for (A) personal and (B) impersonal models. The estimated MSE for personal and impersonal fNIRS/PPI-R-CS models are 0.2921 and 0.1944, respectively. The blue circles show samples and the red stars show the left-out sample.

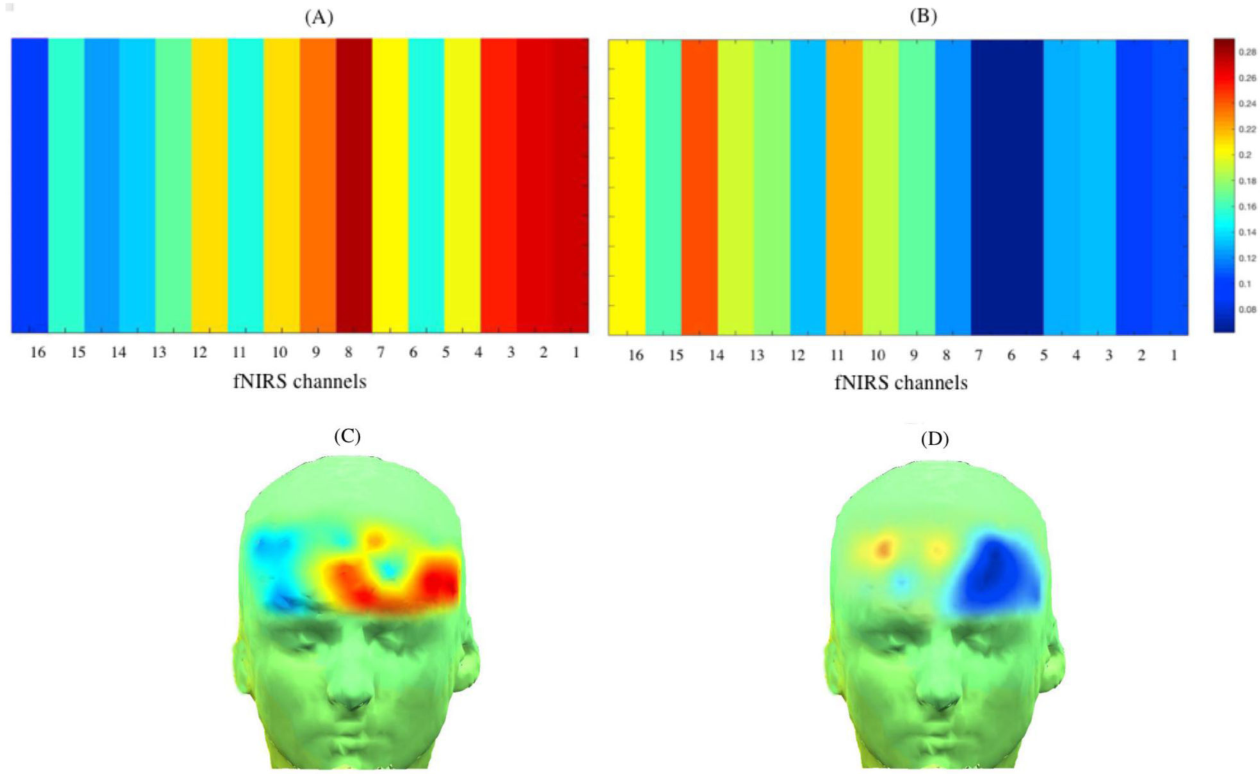

Figure 6.

The fNIRS channels activity map of the first component (component with the highest eigenvalue) for personal (A) and impersonal (B) datasets. (A) shows the left dlPFC (channels 1, 2, and 3) and vmPFC (channels 6, 7, 8 and 9) experience similar dynamics with PPI-R-CS core traits in personal dilemmas, while (B) shows right lateral PFC (channels 14 and 16) and a small region of vmPFC (channel 10) experience the same dynamics as PPI-R-CS psychopathic traits during impersonal dilemmas. Overall, less functional prefrontal dynamics during impersonal dilemmas is observed. (C) and (D) show the head plots corresponding to personal (A) and impersonal (B) strips.

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Table 1.

PPI-R-FS subcategories' means and standard deviations. The mean scores for each core trait were around 50, indicating normal levels of core traits in our participants.

PPI-R-FS	**Self-Centered Impulsivity**	**Fearless Dominance**	**Coldheartedness**
Mean, SD	**48.16 (± 8.53)**	**52.53 (± 10.93)**	**48.38 (± 9.89)**

Table 2.

PPI-R-CS subcategories' means and standard deviations. The mean scores for the core traits were around 50, indicating normal levels of psychopathic traits in our participants.

PPI-R-CS	Machiavellian Egocentricity	Rebellious Nonconformity	Blame Externalization	Carefree Non-planfulness	Social Influence	Fearlessness	Stress Immunity	Cold heartedness	Virtuous Responding	Deviant Responding
Mean, SD	**49.39 (± 10.35)**	**53.16 (± 9.12)**	**47.69 (± 10.16)**	**42.41 (± 8.75)**	**51.33 (± 10.8)**	**52.02 (± 9.92)**	**53.13 (± 11 1)**	**48.38 (± 9.89)**	**55.8 (± 13.81)**	**46.78 (± 5.96)**

Table 3.

PPI-R-CS subcategories and their associated component proportions that play crucial/non-crucial roles in the correlation between linear mixture of fNIRS and PPI-R-CS data. The numbers highlighted in blue are discussed in the text.

PPI-R-CS	Machiavellian Egocentricity	Rebellious Nonconformity	Blame Externalization	Carefree Non-planfulness	Social Influence	Fearlessness	Stress Immunity	Cold heartedness	Virtuous Responding	Deviant Responding
Personal fNIRS	**−0.6305**	**−0.0151**	**−0.0623**	**0.7928**	**0.0653**	**0.3665**	**0.3054**	**0.9187**	**0.0947**	**−0.1108**
Impersonal fNIRS	**0.7776**	**0.6746**	**0.0399**	**0.6272**	**−0.0584**	**0.2810**	**−0.0911**	**0.4929**	**−0.0906**	**−0.3190**