**11 Predicting personality and emotional abilities from brain features using machine learning**

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**Abstract**

This chapter extensively explores the comprehension and prediction of emotional abilities and personality traits based on brain features through the usage of machine learning techniques. Following an introduction to a mathematical-computational conceptualization of the brain and its functions, we provide an overview of unsupervised and supervised machine learning methods for analyzing brain data. The brain can be conceptualized as a mathematical object of N-dimensions that can be broken down into brain states. These brain states can be used to predict psychological variables. Machine learning enables the extraction of predictive functions that map brain states to psychological states. These functions, once discovered, can be used to make predictions in new unobserved cases. Following that, we delve into recent advancements in the field of affective neuroscience, highlighting several recent examples of neuro-predictive models. We commence with models that forecast reappraisal, suppression, and acceptance, which serve as examples of well-established emotion regulation abilities.

We then discuss recent advances in the field of personality neuroscience, presenting a few examples of neuro-predictive models of personality. We delve into discussions about borderline, narcissistic, and anxious personality types. Moreover, we present a study that shows the possibility of predicting the personality of clients from their therapists’ cortical activity. We conclude that both current and prospective applications of machine learning in affective neuroscience present a plethora of opportunities for translational applications.

**11.1 The brain is a mathematical object**

*Molly: Our profile says you're doing everything you can to kill you...*

*Case: Profile?*

*Molly: We have developed a very detailed model.*

*We have broken down your personality into various*

*behavioral modules, with related standard analysis,*

*then recombined everything thanks to military software.*

*You're suicidal, Case. The model gives you a maximum of one month of life.*

*And our medical projection is that you will*

*need a new pancreas within a year.*

*WILLIAM GIBSON, Neuromancer, 1984*

From a biological standpoint, the brain consists of neurons, glial cells, tissues, blood vessels, and various other anatomical components. However, for a cognitive neuroscientist seeking to comprehend how these structures contribute to mental abilities, solely relying on the biological perspective is inadequate. While anatomy and physiology serve as the foundation, they do not directly explain the unfolding of cognitive processes. To gain a comprehensive understanding of the brain, multiple perspectives are required, ranging from biological to cognitive, and even computational approaches. The present chapter begins with the concept of considering the brain as a mathematical object. This perspective allows for the application of mathematical and computational methods to understand and model brain functions. With a mathematical object we intend to have a structure made of mathematical relationships between the subparts. The subparts refer to a large number of dimensions. If we consider, the approximate number of synapses, the brain can be described as a N-dimensional space of circa 1015 dimensions (the state of every synapsis contributes to the structure, and as such it is a dimension with a given range of values). If we consider the neurons, there are 1012 dimensions Usually, in a cognitive neuroscience perspective, we rely on voxels as the minimum unit of analysis, ending up to ~105 dimensions. Voxels can be clustered in brain regions leading to a much lower number of dimensions. Regardless of the level of analysis employed, the brain can be conceptualized as a mathematical structure composed of N dimensions.

What does this complex mathematical structure do? In a computational perspective, this structure performs operations that can be described as computations of functions (Churchland and Sejnowski, 2016). A function can be described as a mapping between elements of one set (the domain) and another set (the range). In other words, a computable function can be specified by a rule that indicates how to transform the first element into the second. In this framework, the brain's states and their transitions represent a system capable of complex computations (Churchland and Sejnowski, 2016), making it a powerful computational entity. To model brain states computationally, neuroscientists use vectors. A vector is an ordered set of numbers that can describe various parameters, such as neuronal firing rates, the grey matter density in voxels, or the connectivity between regions (Churchland and Sejnowski, 2016). A vector represents a brain state in a N-dimensional space (the whole brain). Brain states are points within this space[[1]](#footnote-2). Brain states can be conceptualized as specific arrangements within a part, or the entire, N-dimensional space. These states are associated with, or correspond to, specific psychological functions we perform. This conceptualization is useful for both understanding the brain itself, and the machine learning (ML) analyses when they are applied to the brain. This perspective is indeed coherent with what we do when we analyze brain data with ML methods. In standard frequentist approaches, such as for example the generalized linear model (GLM), we typically begin by examining experimental manipulations (such as stimuli of different categories) and seek to identify corresponding variations in brain signals. Conversely, in machine learning (ML) approaches, we take the opposite approach: we begin with brain states and attempt to predict psychological variables from them. This flow of analysis aligns with the arguments we have presented thus far on brain functioning from a mathematical-computational perspective[[2]](#footnote-3). When we apply machine learning methods to the brain, we aim to predict cognitive states from brain states (intended as specific rearrangements of part of, or the entire, brain)[[3]](#footnote-4). If we denote cognitive states with the greek letter “Ψ” and brain state with “σ”, then when we apply machine learning methods, we aim to predict Ψ from σ[[4]](#footnote-5). See Figure 12.1 for a graphical representation. Going back to the computational perspective, the goal is to derive a function “ that maps brain states (σ) into cognitive states (Ψ)[[5]](#footnote-6). This approach enables the predicting of psychological functions from neural data. The advantage of machine learning is that can be used to predict new cases. In other words, can be used to know which psychological operation is performing in a brain in a given state. This opens up the possibility of creating predictive models of psychological functions, as we will explore in the following sections. Before discussing these results, in the next section we introduce some useful machine learning concepts.

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Descrizione generata automaticamente

**Figure 11.1. Levels of analyses**

**11.2 Machine learning approaches to predict emotions and personality**

Over the past few decades, the field of neuroscience has made substantial strides in unveiling the complex neurobiological mechanisms underlying psychiatric and neurological disorders. However, the translation of research findings into clinical practice remains considerably limited (Prata, Mechelli, & Kapur, 2014; Woo, Chang, Lindquist, & Wager, 2017). One possible reason for this gap is that traditional research methodologies often produce insights at the group level, which, while valuable, do not directly support individual-level clinical decision-making nor prediction of new cases (Arbabshirani, Plis, Sui, & Calhoun, 2017; Mechelli & Viera, 2019). This discrepancy highlights the growing importance of machine learning in healthcare research (Yahata et al. 2017). Machine learning, a subfield of artificial intelligence (AI), has significantly evolved as a discipline aimed at developing intelligent systems capable of autonomously acquiring knowledge and making decisions. This domain focuses on extracting patterns from datasets and leveraging these patterns to forecast outcomes on novel, unseen data (Mitchell, 1997). Central to machine learning is the concept of generalizability, which pertains to the model's ability to apply learned rules from previous data to accurately predict outcomes in new datasets (Domingos, 2012; Mechelli & Viera, 2019). Generalizability serves as a cornerstone in evaluating the efficacy of machine learning models, emphasizing their potential in making reliable predictions across varying scenarios. Machine learning, with its multivariate nature, addresses the limitations of standard statistical approaches by considering variable interrelationships within a unified model, providing a more robust link between neurobiological underpinnings and the phenomenology of the disorder (Wolfers et al., 2018). More importantly, ML tests for generalization to new cases without assuming it as in standard statistical approaches. Indeed, one advantage of such methods relies in their power to extract predictive models from the data. These predictive models can be used to classify patients versus controls, or to predict clinical variables (relapse, treatment responses, symptomatic severity, etc.). In this way, ML's ability to extract predictive models holds promise for enhancing diagnostic accuracy and personalizing treatment strategies (Mechelli & Viera, 2019.

ML methods can be broadly categorized into supervised learning and unsupervised learning (Vu et al., 2018). Specifically, supervised learning involves training a model on labeled data, where the desired output is known. For example, a model might be trained to discriminate patients that suffer from personality disorder based on the underling neural features (Gao et al., 2017). On the other hand, unsupervised learning deals with unlabeled data, aiming to uncover hidden patterns or structures. For instance, clustering algorithms can group patients with similar symptom profiles or brain activity patterns, potentially revealing subtypes of psychiatric disorders (Drysdale et al., 2017). However, supervised methods are often preferred for creating predictive models, especially when the goal is to predict a diagnosis (classification problem), predict a personality trait or investigate a specific emotional ability (regression problem) (Grecucci et al., 2023). One of the most used classes of supervised machine learning are support vector machines (SVM) which are particularly effective in high-dimensional spaces, such as neuroimaging data (Mechelli & Viera, 2019). SVMs work by finding a hyperplane that best separates the data into different classes. The use of kernel functions, such as polynomial, radial-basis function (RBF), and sigmoid, allows SVMs to handle non-linear relationships by transforming the input data into a higher-dimensional space where a linear separator can be applied. One of the key advantages of SVMs is their ability to highlight which features (variables) are most important in distinguishing between classes. This feature’s importance is crucial in neuroimaging, where understanding which brain regions are most predictive of a condition can provide insights into the underlying neurobiology (Orru et al., 2012)

To further enhance the insights gained from neuroimaging data, data-driven multimodal fusion approaches integrate information from features from different neuroimaging modalities (e.g., MRI, fMRI, EEG) as well as genetic data (Mechelli & Viera, 2019). These methods, such as canonical correlation analysis (CCA), joint independent component analysis (jICA), and parallel ICA (pICA), enable the combination of complementary data features to enhance the detection of disease-related patterns or psychological construct (Sui et al., 2020). By combining the information of each modality, fusion methods improve the robustness and reliability of neuroimaging biomarkers, facilitating more accurate diagnoses and treatment plans (Baggio et al., 2023; Grecucci et al., 2023; 2024; Jornkokgoud et al., 2024; Monachesi et al., 2024).

In the upcoming sections, we delve into recent neuro-predictive models of emotional abilities and personality traits that leverage machine learning methods.

**11.3 Predicting emotional abilities**

Emotions are multi-dimensional psycho-biological responses elicited by significant environmental triggers that produce changes in our subjective feelings, physiological responses, and behavioral manifestations (Grecucci et al., 2023; Lazarus, 1991; Mauss et al., 2005; Scherer et al., 2001). Central to our understanding of the emotional response, is the concept that in normal conditions, the emotional intensity correlates with the magnitude of the emotionality conveyed by the stimulus that elicited the response (Frederickson et al., 2018; Grecucci et al., 2020). Following Fechner's law describing the psychophysical response to sensory input, we can model the emotional response (ye) as a function of the stimulus relevance (xs) with the formula:

ye = log(xs)

This model suggests that low-intensity stimuli trigger mild emotional reactions, whereas high-intensity stimuli induce intense emotional reactions (Grecucci et al., 2020). The response pattern aligns with the logarithmic scaling of sensory perception. Specifically, the response curve steeply ascends at lower stimulus values and flattens at higher levels, agreeing well with the laws of psychophysics discovered by Fechner. However, the dynamics of emotional response in daily life and in clinical settings show much more complexity than this simplified model (Grecucci et al., 2020). Variability in responses may therefore not only index proportionality to the stimulus objective intensity, but also intrinsic individual differences (Dadomo et al., 2019). Such deviations can be modelled by modifying the original equation to include several factors (see Grecucci et al., 2020 for a complete discussion of this model). We start by considering the “intensity” factor η, resulting in the modified equation:

ye = log(xs) + η

where η denotes a variation of intensity that can either affect ye in a positive or negative way, indicating an enhanced or diminished emotional response's intensity relative to the stimulus (see Figure 12.2 A). Another relevant aspect is the temporal dynamics of the emotional response. Indeed, responses can be either almost immediate, or preceding the stimulus, or largely delayed. To integrate these temporal disparities, the model can be broadened as follow:

ye =log(xs + 𝜏)+ η

where 𝜏 represents the time shift, with negative values indicating anticipatory responses (𝜏 < 0) and positive values reflecting delayed responses (𝜏 >0) (see Figure 12.2 B).

Another important aspect that must be considered is the speed at which emotional responses escalate to their peak. This variability in the emotional response requires further modification in the equation:

ye = ω\*log(xs + 𝜏)+ η (1)

Here, ω indicates the growth rate of the response, with values less than one indicating a rapid escalation and values greater than one a slower ascent (see Grecucci et al., 2020 for a graphical representation of this equation) (see Figure 12.2 C). Equation (1) describes a range of variations that we can observe in the clinical settings. Significant variation of the variables η, 𝜏, and ω collectively define what we indicate by the term "emotional dysregulation”. These factors may individually or collectively contribute to pathological emotional responses, such as those that are prematurely triggered, excessively intense, or rapidly peaking, necessitating targeted clinical attention (Dadomo et al., 2018). Indeed, challenges in managing emotions are linked to various psychological disorders (Kring & Sloan, 2009; Sheppes et al., 2015; Dadomo et al., 2018; Frederickson et al., 2018; Grecucci et al., 2020). Given the widespread emotion regulation challenges across psychological disorders, clinicians have begun to incorporate a range of emotion regulation strategies into their therapeutic methods (Leahy et al., 2011; Messina et al., 2013; Dadomo et al., 2016, 2018; Frederickson et al., 2018). From a translational research perspective, the ability to predict emotion regulation abilities holds promise for improving the diagnosis and treatment of individuals facing emotion regulation challenges. Machine learning can serve as a valuable tool in this endeavor, offering sophisticated algorithms capable of analyzing complex brain data to identify patterns and predict emotion regulation abilities. By leveraging machine learning techniques, researchers can develop predictive models that aid clinicians in identifying individuals at risk of emotional dysregulation and tailor interventions to meet their specific needs. This approach enhances the precision and effectiveness of clinical interventions, ultimately improving outcomes for individuals struggling with emotion regulation difficulties.

Before discussing these studies, we provide an introduction to the main strategies used in the following studies.

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**Figure 11.2.** Family of equations to graphically represent the variations in emotional response according to the η (A) , 𝜏 (B) , and ω (C) factors.

Reappraisal is referred to as “construing a potentially emotion-eliciting situation in non-emotional terms” (Gross, 1998; 2002). It is an antecedent-focused regulation strategy, modifying the emotion before it fully develops. Research has shown that reappraisal effectively reduces the intensity of negative emotional reactions and lowers the respiration rate. It also reduces the behavioral expressions associated with negative emotions, moderates physiological responses, and enhances well-being (Gross, 2002, 2015; Wolgast et al., 2011; Goldin et al., 2019).

Suppression is categorized as a response-focused emotion regulation strategy, involving modifying emotional responses after they have fully emerged. It is defined as an effort to inhibit the behavioral display of current emotions (Gross & Levenson, 1993). Several studies reveal that suppression leads to a reduction in positive emotional experiences while leaving negative emotions unaffected. Additionally, it has negative physiological impact (Gross & Levenson, 1993, 1997; Gross, 2002; Mauss et al., 2005; Brans et al., 2013).

Acceptance is defined as “the active and ware embrace of private experiences without unnecessary attempts to change their frequency or form” (Hayes et al., 2012). It is an attitude of openness and curiosity towards the ongoing stream of thoughts and sensory experiences (Grecucci et al., 2015; Goldin et al., 2019). Acceptance is considered as an adaptive emotion regulation strategy, positively linked to well-being (Aldao et al., 2010).

For what concerns the application of machine learning methods to predict emotional regulation abilities from neural features, one of the first attempts was made by Pappaianni and colleagues who used an unsupervised machine learning approach, known as source-based morphometry (SBM, Xu et al., 2009), based on Independent Component Analysis (ICA), to explore individual differences in structural brain characteristics associated with reappraisal usage. In their study, 37 participants were categorized into low and high reappraisal groups based on their scores from the Emotion Regulation Questionnaire (ERQ; Gross & John, 2003). The findings indicated a greater concentration of grey matter in a network encompassing the frontal, temporal, and parietal regions in low reappraisers compared to high reappraisers.

More recently, a pioneering study by Ghomroudi and colleagues (2023) developed a neuro-predictive model of both reappraisal and suppression usage able to successfully predict new cases. This study applied a combination of unsupervised and supervised machine learning algorithms to the structural MRI scans of 128 individuals. Initially, unsupervised machine learning in the form of group ICA, was used to segment the brain into naturally occurring grey matter networks. Subsequently, supervised machine learning in the form of boosted trees, was applied to predict individual differences in reappraisal and suppression. Two predictive models were extracted. The first model included a temporo-parahippocampal-orbitofrontal network (Independent component IC13) that correctly predicted individual differences in reappraisal use. The second model included insular and fronto-temporo-cerebellar networks (Independent component IC8) that successfully predicted suppression usage. Of note, psychological factors such as the level of anxiety, the opposite strategy usage, and specific emotional intelligence indicators, contributed to the predictive models.

In another study, Grecucci and colleagues (Grecucci et al., under review) used a data fusion machine learning technique (mCCA-jICA) to identify combined grey and white matter networks associated with high and low acceptance ability. This study revealed that two covarying GM-WM networks distinguish high accepters from low accepters. The first network demonstrated decreased GM-WM concentration in a fronto-temporal-parietal circuit that overlaps significantly with the Default Mode Network. The second network showed increased GM-WM concentration in the orbito-frontal, temporal, and parietal regions associated with the Central Executive Network. Psychologically, high accepters showed greater openness to experience compared to low accepters. These results suggest that high accepters and low accepters differ in their neural and psychological mechanisms, supporting and extending previous research on the significance of acceptance as a strategy linked to well-being.

Beside structural evidence, the contribution of functional networks (resting state macro-networks) to emotion regulation has been recently investigated. Ghoumroudi and colleagues (under review) conducted a functional connectivity analysis on resting-state data from 134 individuals. Employing group-ICA an unsupervised machine learning approach, and regression analyses, authors identified resting-state networks that predicted acceptance and reappraisal abilities. Acceptance was associated with the Executive, Affective (including subcortical emotion-related areas), and Sensorimotor networks, while Reappraisal was linked to the Sensorimotor network.

In summary, machine learning methods have proven successful in predicting emotional abilities such as emotion regulation strategies usage.

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| **Table 1. Emotion Regulation** | | |
| **Authors** | **Main findings** | **Year of publication** |
| Ghomroudi et al. | Combined unsupervised and supervised machine learning algorithms on structural MRI scans of 128 individuals was applied. Initially, group ICA segmented the brain into grey matter networks. Then, boosted trees predicted individual differences in reappraisal and suppression. Two models emerged: one involving a temporo-parahippocampal-orbitofrontal network (IC13) for reappraisal prediction, and another involving insular and fronto-temporo-cerebellar networks (IC8) for suppression prediction. Psychological factors, including anxiety levels, opposite strategy usage, and specific emotional intelligence indicators, contributed to these models | 2023 |
| Grecucci, et al. | The mCCA-jICA data fusion technique was applied to 128 MRI scans of healthy individuals to identify combined grey and white matter networks associated with acceptance ability. Two covarying GM-WM networks differentiated high accepters from low accepters. The first network showed decreased GM-WM concentration in a fronto-temporal-parietal circuit, overlapping significantly with the default mode network. The second network showed increased GM-WM concentration in the orbito-frontal, temporal, and parietal regions, linked to the central executive network. High accepters also demonstrated greater openness to experience. These findings highlight distinct neural and psychological mechanisms between high and low accepters, emphasizing the importance of acceptance in well-being | 2024 (under review) |
| Ghomroudi, et al. | A functional connectivity analysis was conducted on resting-state data from 134 individuals. Using group-ICA, and regression analyses, resting-state networks were identified that predicted acceptance and reappraisal abilities. Acceptance was associated with the executive, affective, and sensorimotor networks, while reappraisal was linked to the sensorimotor network. | 2024 (under review |

**11.4 Predicting personality traits**

In this section, we delve into recent developments within personality neuroscience that have harnessed the power of machine learning methodologies to construct neuro-predictive models of personality traits. Specifically, we focus on abnormal personality traits, a domain that has garnered increasing attention due to its clinical relevance and impact on individuals' well-being (Langerbeck et al., 2023). By employing machine learning techniques, researchers have been able to analyze complex patterns in neurobiological data and identify neural signatures associated with various personality traits, including those considered atypical or pathological (Grecucci et al., 2023; 2024; Jornkokgoud et al 2023; 2024). Such neuro-predictive models offer valuable insights into the underlying neural mechanisms of abnormal personality traits, shedding light on the neurobiological basis of conditions such as personality disorders. Furthermore, the application of machine learning in personality neuroscience opens up new avenues for personalized medicine and targeted interventions. By leveraging neuro-predictive models of personality, clinicians may be better equipped to identify at an early stage individuals at risk of developing personality disorders. Individuals with Personality pathologies exhibit an enduring pattern of internal experiences and behaviors that significantly diverge from the societal norms within their culture (American Psychiatric Association, 2013). Notably, those diagnosed with borderline personality disorder (BPD) often show problems in emotion expression and mood regulation (Mendez-Miller et al., 2022). This is characterized by an unstable pattern of impulsive control, manifesting in both interpersonal relationships and behavior, that includes impulsive aggressive outbursts and engagement in health-sabotaging activities (i.e., cutting) (Dadomo et al., 2016; De Panfilis et al., 2019; Mendez-Miller et al., 2022). A precise and psychiatric diagnosis is often complex and difficult due to several issues (Grecucci et al., 2022; Rao et al., 2020). First, the presented symptoms are strongly fluctuating within patients, increasing their psychiatric vulnerability (Choi-Kain et al., 2020). Second, the currently used classification manuals use a categorical approach to classify personality disorders. In contrast, personality is usually identified on a spectrum, using five domains of personality (Ashton, 2017). Another issue with the classification problem is the immense overlap in symptoms between the different categories of personality disorder (Siefert et al., 2022). Lastly, the diagnosis of BPD relies on observable behavior. Affective neuroscience has emerged as a method to identify neurobiological markers which serve as an objective tool to diagnose a PD via machine learning methods (Grecucci et al., 2022). Previous studies suffered from many limitations such as the use of mass univariate analysis, which can only look at each voxel separately, ignoring statistical relationships between voxels (Lapomarda et al., 2021; Sorella et al., 2019). Another disadvantage is the consideration of the average of individuals within each group, ignoring individual variances. Finally, in the mentioned studies the results have not been tested on new cases, thus no conclusion about generalizability can be made. Machine learning is a promising tool to overcome these limitations. Three studies have used machine learning to investigate the neural correlates of BPD. Grecucci et al. (2022) constructed a predictive model of Border Personality Disorder (BPD) by using Multiple Kernel learning, a form of Support Vector Machine for classification. This approach identifies brain areas that contribute to the model as the most relevant source for classification by using whole-brain pattern-based information (Mourao-Miranda et al., 2012). The authors were able to outline a specific neuronal circuit, including the right Putamen, the left thalamus, the right fusiform gyrus, the right amygdala, the lingual gyrus, the right middle, and superior orbitofrontal cortex (OFC), the left pallidum, the left fusiform gyrus, and portions of the cerebellum, supporting previous findings. In another study, Grecucci et al. (2023) provided further strength and insight into these findings. By applying a combination of supervised (Random Forest) and unsupervised ML (mCCA+jICA) the brain was parceled into networks of covarying grey and white matter concentration. Second, the authors were able to build from this a predictive model which was able to classify individuals with BPD. The use of machine learning in this study had the advantage that it was able to clearly unravel any potential ambiguity and that the found networks were able to correctly classify new unobserved cases. A more recent study by Langerbeck et al. (2023) investigated the neural correlates of borderline personality trait (BPT) using a subclinical sample. By applying Kernel Ridge Regression (KRR), a form of Support Vector Regression, the authors were able to provide a distinctive circuit, based on a whole brain level, including the frontal and parietal regions, as well as the Heschl’s area, the thalamus, the cingulum, and the insula. Furthermore, BPT predictions increase when only the regions limited to the brain circuit derived from the BPD model (Grecucci et al., 2022) are considered, thereby confirming a certain overlap in brain structure between subclinical and clinical samples. This study shows that ML is able to classify new cases when using dimensional scales, like personality traits.

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| **Table 2. Borderline personality** | | |
| **Authors** | **Main findings** | **Year of publication** |
| Grecucci, et al. | 20 patients with BPD, 30 patients with bipolar disorder (BD), and 45 healthy controls, structural MRI, were analyzed with Multiple Kernel Learning (MKL). BPD was correctly classified (80% accuracy) against HC by a circuit, including the basal ganglia, amygdala, portions of the temporal lobes and of the orbitofrontal cortex. By contrasting BPD with BD a more specific circuit for BPD could be outlined. The authors suggest that BPD can be characterized by anomalies in a cortico-subcortical circuit related to affective instability. | 2022 |
| Grecucci, et al. | 20 patients with BPD and 45 healthy control participants HC), structural MRI (grey and white matter), were analyzed with multimodal canonical correlation analysis, random forest. Two GM-WM covarying circuits, including the basal ganglia, amygdala, portions of the temporal lobes and of the orbitofrontal cortex, correctly classified BPD against HC. These circuits are affected by child traumatic experiences (e.g. emotional and physical neglect, physical abuse) and were predictive of symptoms severity (interpersonal and impulsivity domains). The authors suggested that these results show that BPD is characterized by anomalies in GM and WM circuits that are related to early traumatic experiences. | 2023 |
| Langerbeck, et al. | Strucutral scans of 135 participants were analyzed with Kernel Ridge Regression. At a whole brain level, a circuit including frontal and parietal regions, the Heschl’s area, thalamus, cingulum, and insula, is predictive of borderline traits. BPT predictions increased when only a BPD circuit was considered. The authors confirmed a certain overlap in brain structure between subclinical and clinical samples. The default-mode network predicts BPT, confirming previous observations on its role in the BPD. | 2023 |

Another line of research tried to develop neuro-predictive models of narcissistic personality traits. Narcissism is a complex personality trait characterized by various facets, including impaired relationship functioning, inflated self-perceptions, and intrapersonal and interpersonal mechanisms aimed at preserving these perceptions (Campbell et al., 2011; Twenge & Campbell, 2003). The term Narcissism encompasses a broad spectrum of personality functioning that impacts self-worth, coherence, uniqueness, attachment in relationships, and empathy (Ronningstam, 2011). Pathologically, Narcissism can manifest as grandiose or vulnerable subtypes, each with distinct characteristics (Miller et al., 2011). Neuroscientific exploration of narcissism is a burgeoning field aiming to understand the neural underpinnings of this personality trait and disorder. For instance recently, Jornkokgoud and colleagues (2023) developed a predictive model of narcissism based on neural and psychological features underlying individual differences in narcissistic personality traits among 135 healthy participants. They used Kernel Ridge Regression (KRR) and Support Vector Regression (SVR) that successfully associated certain brain regions, including the lateral and middle frontal gyrus, angular gyrus, Rolandic operculum, and Heschl’s gyrus, with individual differences in narcissistic traits. In another study, Jornkokgoud and colleagues (2024) capitalized on a combination of unsupervised and supervised machine learning methods to investigate the joint contributions of grey matter (GM) and white matter (WM) to narcissistic personality traits (NPT). Brain scans from 135 participants were first decomposed into eight independent networks of covarying GM and WM using parallel ICA. Stepwise regression and Random Forest algorithms were then employed to predict NPT. Results revealed a distributed network with GM alterations in fronto-temporal regions, the insula, and the cingulate cortex, along with WM alterations in cerebellar and thalamic regions. Of note this network was specific for narcissistic traits and did not predict other personality traits used as controls (histrionic, paranoid, and avoidant). These findings hold promise for advancing our understanding of personality traits and potentially identifying brain biomarkers to predict narcissistic personality traits.

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| **Table 3. Narcissistic personality** | | |
| **Authors** | **Method and Main Findings** | **Year of Publication** |
| Jornkokgoud, et al. | Structural scans of 135 healthy individuals were considered. Brain regions such as the orbitofrontal cortex, Rolandic operculum, angular gyrus, rectus, and Heschl’s gyrus were significant predictors of narcissistic traits. The study employed two supervised machine learning methods: Kernel Ridge Regression (KRR) and Support Vector Regression (SVR). Personality traits such as Borderline, Antisocial, Addicted, Negativistic, and Insecure (from PSSI), Machiavellianism and Narcissism (from SD3), and Openness, Agreeableness, and Conscientiousness (from NEO-PI-R) were significant predictors. | 2023 |
| Jornkokgoud, et al. | Structural scans of 135 healthy individuals were taken into cosideration. This study used a combination of unsupervised and supervised machine learning methods to analyze the contributions of grey matter (GM) and white matter (WM) to narcissistic personality traits (NPT). Parallel Independent Component Analysis (p-ICA) was used to decompose brain scans into networks of covarying GM and WM. Stepwise regression and Random Forest regression were employed to predict NPT. A distributed network including GM alterations in fronto-temporal regions, insula, and cingulate cortex, and WM alterations in cerebellar and thalamic regions predicted NPT but not other personality traits (histrionic, paranoid, avoidant). | 2024 |

Another recent line of research tested the hypothesis that personality disorders could be predicted from the brain patterns of therapists interacting with their patients. Tanzilli et al. (2023) demonstrated that subjective feelings and cortical responses (EEG) of therapists could predict the personality disorders of their clients. Fourteen therapists observed videos of patients with narcissistic, histrionic/borderline, and depressive personality disorders. They then completed assessments and underwent high-density EEG while viewing images of the patients' faces. Decision trees successfully predicted the patients' personality disorders with high accuracy (80% to 100%) based on therapists' subjective responses and EEG data. For example, criticized/devalued reactions identified narcissistic patients, while sexualized reactions predicted histrionic/borderline disorders. From a neural perspective, a key finding of this investigation was the ability of the late positive potential amplitude (LPP) within the hippocampus to effectively differentiate between personality disorders. Specifically, the initial LPP sub-component (Late Component 1, LC1) was triggered by the visual presentation of narcissistic versus depressive patients. The intermediate sub-component (LC2) differentiated between narcissistic and histrionic/borderline patients. The most durable LPP sub-component (LC3) was significant in distinguishing between depressive and histrionic/borderline patients. These results highlight the potential of ML methods to assist clinicians in diagnosing their clients based on their own subjective and neural responses.

Anxiety represents a highly diversified condition that includes intense adverse feelings of tension, apprehension, and worried thoughts, with additional physiological changes such as increased blood pressure and heart rate, dizziness, sweating and nausea (Byrne & Rosenman, 1990)(Yang et al., 2021). From a clinical point of view, anxiety diagnosis is mainly based on the Structured Clinical Interview for DSM (SCID), a semi-structured interview that is able to assess different anxiety disorders, i.e. Generalized Anxiety Disorder (GAD), Panic Disorder, Social Anxiety Disorder (SAD), Agoraphobia, Specific Phobia, Selective Mutism, Separation Anxiety Disorder, Substance/medication-induced Anxiety Disorder, Anxiety disorder due to another medical condition and other specified/unspecified Anxiety Disorder (American Psychiatric Association, 2013). In non-clinical settings anxiety is instead studied through self-report questionnaires, and can be categorized both as a state, intended as a transient feeling, and a trait, intended as a stable predisposition to experience negative apprehensive affections (Spielberger et al., 1983). Anxiety trait can be considered a stable personality trait. Besides studies applying machine learning methods to fully diagnosed anxiety disorders, some recent studies have tried to develop neuro-predictive models of the anxious personality. For example, Saviola and colleagues have recently applied an unsupervised machine learning method based on group ICA on both structural and functional resting state MRI to a sample of 42 healthy individuals to investigate the relation between anxiety and brain macro-networks. They found that trait anxiety correlates with grey matter structural covariance of the default mode network and salience network, and correlates with resting-state functional connectivity of the frontal default mode network frontal regions, while state anxiety is associated only with resting-state functional connectivity of the default and salience networks (Saviola et al., 2020). Chavanne and colleagues investigated structural correlates of future anxiety symptoms during adolescence, using a voting classifier with Random Forest, Support Vector Machine and Logistic Regression algorithms. In a sample of 878 subjects they found that the caudate and pallidum grey matter volume at age 14 contributes to the prediction of GAD at age 18-23, with larger volumes associated with future GAD diagnosis (Chavanne et al., 2023). Most recently, Baggio et al., used a data fusion ML approach by combining grey and white matter data identifying covarying networks crucial for trait anxiety prediction through Parallel ICA and decision trees, which included the parietal, temporal and frontal regions such as the postcentral gyrus, the precuneus, the anterior cingulate and the middle temporal gyrus (Baggio et al., 2023). This study marks a significant departure from earlier single-modality studies, emphasizing the importance of integrating multiple brain modalities in understanding anxiety. A further investigation of trait anxiety individual differences has been done examining a larger sample of 554 individuals, particularly focusing on late adolescents and young adults, with the use of Parallel ICA (Baggio et al., under review). This study represents a great advancement not only because of the large sample size used, but also because it offers critical insights into anxiety's unique characteristics of a particular developmental phase, essential for creating accurate predictive models in non-clinical populations.

In another study, Wen et al. (2022) integrated white and grey matter network data for functional connectivity analysis in SAD patients, finding a disrupted connection in many areas such as the limbic regions, prefrontal and temporal areas (Wen et al., 2022).

Focusing only on white matter, Yoo and colleagues analysed DTI data from 148 healthy participants, performing a connectome-based predictive modelling (CPM), using a younger adult group (n= 94) and an older adult group (n= 54) (Yoo et al., 2022). The connectome-wide data-driven CPM analysis identified several regions to predict trait anxiety levels, specifically there was a decreased structural connectivity among the lateral orbitofrontal cortex, the amygdala, the parahippocampal gyrus, the pallidum and the temporal pole in highly anxious younger adults. When older adults were included in the analysis, an increased structural connectivity of frontotemporal and frontolimbic circuits was predictive of higher trait anxiety. No networks significantly predicted trait anxiety scores when only older adults were considered.

For studies focusing on task related functional MRI, Portugal and colleagues (2019) predicted trait anxiety from brain activation during a dynamic face task, identifying regions like the rectus, inferior occipital cortex, cerebellum, and inferior and orbital frontal cortex as predictive of anxiety scores (Portugal et al., 2019).

Finally, Baggio et al.’s recent study (2023) focused on triple network functional connectivity in young adults, emphasizing the importance of a differential analysis of non-clinical anxiety in this distinct sensitive developmental phase. Notably, the authors identified an increased connectivity of all the triple network sub-components (salience, default, and central executive networks) in high-anxious individuals. See Table 4.

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| --- | --- | --- |
| **Table 4. Trait anxiety** | | |
| **Authors** | **Method and Main Findings** | **Year of Publication** |
| Portugal, et al. | Functional MRI scans of 82 patients and 72 healthy controls were taken into consideration. Whole-brain neural activity related to dynamic emotional face processing was able to predict self-report anxiety | 2019 |
| Saviola, et al. | Structural and functional MRI scans of 42 subjects. Trait anxiety was associated to structural covariance of the DMN and resting-state functional (rs-FC) connectivity of the DMN within frontal regions. State anxiety instead was associated only to rs-FC of SN and DMN | 2020 |
| Wen, et al. | Structural and functional MRI scans of 48 SAD patients, and 48 healthy controls were analyzed. SAD patients displayed a disrupted connection between the limbic and dorsal prefrontal, lateral temporal, and sensorimotor networks, and between the visual and sensorimotor networks. Moreover, there were negative correlations between HAMD scores and limbic-dorsal prefrontal and limbic-sensorimotor networks, and between illness duration and sensorimotor-visual networks | 2022 |
| Yoo, et al. | Diffusion weighted imaging scans of 148 subjects. Networks that predicted trait anxiety differ across age groups. Specifically, a negative network, which shares overlapping features with the amygdala-prefrontal circuitry, was present in 20–30 years of age young adults, whereas a positive network highlighted by frontotemporal and frontolimbic connectivity was present when both younger and older adults (20–80 years of age) are considered | 2022 |
| Chavanne, et al. | Structural MRI scans of 156 patients with clinical anxiety, and 424 healthy controls. MRI regional volumes of caudate and pallidum improved prediction performance of GAD | 2023 |
| Baggio et al. | Structural MRI scans of 158 subjects. Two covarying grey and white matter networks predicted trait anxiety levels, including precuneus, postcentral gyrus, anterior cingulate and superior temporal gyrus | 2023 |
| Baggio, et al | Structural MRI scans of 554 subjects. Higher anxious individuals exhibited a fronto-parieto-cerebellar network with decreased grey matter concentration, linked to bodily awareness and threat modulation, and a parieto-temporal network with increased white matter concentration, emphasizing insula and precuneus role | 2024 (under review) |

**11.5 Conclusion**

Integrating AI and computational methods into neuroscience provides a powerful framework for understanding the brain and extracting predictive models of psychological functions. By viewing the brain as a mathematical object that performs computational operations, we can develop predictive models that bridge the gap between biological structures and cognitive functions. This approach not only advances scientific knowledge but also opens new avenues for treating neurological and psychological disorders. These methods enhance the ability to identify robust biomarkers, improve diagnostic accuracy, and personalize treatment strategies. In conclusion, the integration of machine learning techniques into the investigation of neural features of personality traits holds the promise to revolutionize our comprehension of personality and opens up the possibility of making predictive models. By elucidating the neural correlates of these traits, researchers can gain a deeper understanding of their aetiology and pathophysiology, which is crucial for informing diagnostic and therapeutic strategies.

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1. Whether this N-dimensional space can be described mathematically as a Hilbert space (H), e.g. a generalization of Euclidean space to infinite dimensions, or any other mathematical space, is beyond the scope of this chapter. However, if we assume that H is a good approximation of the N-dimensional space that describes the brain, the following considerations apply. H is a vector space that allows for geometric calculations in multidimensional spaces. Brain states can be represented as subspaces within the Hilbert space. The elements of H are denoted as |u⟩ a "ket" vector in Dirac notation. [↑](#footnote-ref-2)
2. This perspective is coherent with the Bayesian approaches and predictive coding theories to the brain. [↑](#footnote-ref-3)
3. Again, this perspective differs from the standard brain analyses for which we start from cognitive stimuli to see how they affect the brain signal (GLM analysis). [↑](#footnote-ref-4)
4. In Hilbert terminology, we predict Ψ from |u⟩, part of H. [↑](#footnote-ref-5)
5. In Hilbert space terminology this is equivalent to finding the operator “O” that, when applied to |u⟩ returns Ψ. Formally, O|u⟩ = Ψ. [↑](#footnote-ref-6)