Title?

Table of Contents

[Introduction 4](#_Toc195192981)

[Obsessive-Compulsive Disorder 4](#_Toc195192982)

[Neurobiology of OCD 4](#_Toc195192983)

[Structural Brain Abnormalities 7](#_Toc195192984)

[Informant Discrepancies 7](#_Toc195192985)

[Statistical Learning 9](#_Toc195192986)

[Learning methods 9](#_Toc195192987)

[Linear Model 9](#_Toc195192988)

[Decision Trees 10](#_Toc195192989)

[Boosting 11](#_Toc195192990)

[The present study 13](#_Toc195192991)

[Research question 13](#_Toc195192992)

[Methods 14](#_Toc195192993)

[Data Source and Collection Procedures 14](#_Toc195192994)

[Data acquisition 14](#_Toc195192995)

[Structural MRI 14](#_Toc195192996)

[Preprocessing sMRI 16](#_Toc195192997)

[Brain Segmentation 16](#_Toc195192998)

[Regions of Interest 17](#_Toc195192999)

[Demographics and categorical diagnosis 17](#_Toc195193000)

[Self and Parental Reports of dimensional diagnosis 18](#_Toc195193001)

[Parent-Reported Child Behavior Checklist 18](#_Toc195193002)

[Self-Reported Brief Problem Monitor 19](#_Toc195193003)

[Participants 20](#_Toc195193004)

[Modelling approach 23](#_Toc195193005)

[Training 23](#_Toc195193006)

[Testing 23](#_Toc195193007)

[Results 24](#_Toc195193008)

[ 24](#_Toc195193009)

[Training 24](#_Toc195193010)

[Testing 25](#_Toc195193011)

[Discussion 26](#_Toc195193012)

[References 28](#_Toc195193013)

Introduction

Obsessive-Compulsive Disorder

Obsessive-compulsive disorder (OCD) is recognized as a prevalent and persistent neuropsychiatric condition, impacting an estimated 2% to 3% of individuals worldwide (de Mathis et al., 2013). Almost half of adult patients with OCD report symptom onset during childhood or adolescence, with prevalence rates in these age groups ranging from 1% to 4% (Nazeer et al., 2020). OCD is a clinically and etiologically highly heterogeneous disorder, characterized by various overlapping symptom dimensions (Bragdon & Coles, 2017). Obsessive-Compulsive Disorder (OCD) is defined in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) as the presence of obsessions, compulsions, or both. Obsessions are recurrent, intrusive, and unwanted thoughts, urges, or images that typically cause significant anxiety or distress, and which the individual attempts to ignore or neutralize. Compulsions are repetitive behaviors or mental acts performed in response to obsessions or rigid rules, aimed at reducing distress or preventing a feared outcome, though they are not realistically connected to the outcome or are clearly excessive. These symptoms are time-consuming or cause clinically significant distress or impairment in functioning (American Psychiatric Association, 2013). These symptoms cause significant distress or impairment in social, occupational, or other important areas of functioning. It is unique among mental illnesses in that it exhibits both externalizing and internalizing symptom domains (Guzick et al., 2019). Internalizing features, such as anxiety and obsessive thinking, typically manifest as avoidance and withdrawal, while externalizing characteristics; like compulsive or ritualized behavior, are more overt and behaviorally disruptive (Achenbach, 2009; Shephard et al., 2021). Conceptualizing OCD through this dual framework offers a more nuanced understanding of its clinical presentation and has important implications for treatment planning. This framework is therapeutically beneficial and supported by empirical research (Kessler et al., 2011; Slade & Watson, 2006).

Neurobiology of OCD

Advances in neuroimaging, particularly magnetic resonance imaging (MRI), have elucidated the brain's role in OCD (de Wit et al., 2014; Hu et al., 2017; Picó-Pérez et al., 2020). The cortico-striato-thalamo-cortical (CSTC) model is the most widely accepted explanation for the neurobiological underpinnings of OCD, describing the disorder as a dysfunction within the CSTC circuit (Graybiel & Rauch, 2000; van den Heuvel et al., 2016). The CSTC consists of the thalamus, basal ganglia, anterior cingulate cortex, and orbitofrontal cortex (OFC) (Brennan & Rauch, 2017). Primarily, the CSTC model attributes compulsive behaviors as failures in inhibitory control, where these distinct neural A diagram of a brain

AI-generated content may be incorrect.pathways struggle to suppress unwanted thoughts and actions effectively.

***Figure. 1*** *Neural Circuits Involved in Obsessive-Compulsive Disorder: Brain Regions and Connectivity. (1) The Fronto-Limbic Circuit consisting of the amygdala and ventromedial prefrontal cortex (vmPFC). (2) The Sensorimotor Circuit consisting of the supplementary motor area, putamen, pallidum, and thalamus. (3) The Ventral Cognitive Circuit consisting of the inferior frontal gyrus (IFG), ventrolateral prefrontal cortex, subthalamic nucleus (STN), and ventral caudate. (4) The Ventral Affective Circuit consisting of the orbitofrontal cortex (OFC) and nucleus accumbens (NAcc). (5) The Dorsal Cognitive Circuit consisting of the dorsolateral prefrontal cortex (dlPFC) and dorsomedial prefrontal cortex (dmPFC). The visual representation taken from Shephard et al. (2021).*

Building upon the CSTC model, a more recent neurocircuit-based approach has been developed to account for the diverse symptom profiles observed in OCD (Shephard et al., 2021). This expanded model incorporates additional circuits between regions involved in emotion regulation, habit formation, sensory processing, and reward sensitivity. As illustrated in figure 1, this framework by van den Heuvel et al. (2016) describes OCD as dysfunction within five circuits, where OCD symptoms are mediated by partially distinct neural systems (van den Heuvel et al., 2009). Although each circuit is described as associated to a particular symptom dimension relevant to OCD, it is important to recognize their interconnected nature rather than viewing them in isolation. These circuits offer a more nuanced understanding of how OCD symptoms manifest, highlighting the complexity of interactions between multiple brain regions. This model is especially relevant for adolescents because their brains are still developing, particularly the prefrontal cortex, which governs impulse control and emotional regulation (Casey et al., 2008).

These neural circuits are connected to the diverse symptoms observed in OCD. For instance, (1) the fronto-limbic circuit is involved in regulating fear and emotional responses. Hyperactivity within this circuit can lead to intrusive thoughts and potentially trigger obsessions due to impaired top-down emotional regulation (Milad et al., 2013). The amygdala-prefrontal connectivity has been found to be predictive of therapy outcomes for OCD in youth (Cyr et al., 2021). Meanwhile, dysfunction in the (2) sensorimotor circuit, involved in integration of motor behavior and sensory input, explains why some OCD symptoms stem from sensory-driven urges, such as "not-just-right" feelings, and averse or uncomfortable sensations that drive compulsions like excessive touching or arranging objects (Stern et al., 2025). Additionally, habit formation, which is also implicated in this circuit, can cause compulsive behaviors to become automatic, persisting beyond their initial triggers. The (3) ventral cognitive circuit plays a major role in self-regulation, acting as a "braking system" for inhibiting inappropriate actions.; Ddysfunction here may prevent individuals from stopping compulsions even when they recognize them as irrational (van den Heuvel et al., 2016). The (4) ventral affective circuit is involved in reward processing and motivation, where compulsions can become self-reinforcing behaviors, thus may not just alleviate anxiety but become rewarding behaviors themselves, reinforcing habitual and compulsive loops of the sensorimotor circuit. Clinical studies have reported heightened connectivity between the NAcc and other reward-processing regions, such as the OFC during resting-state brain activity, with this increased connectivity correlating with the severity of OCD symptoms (Xie et al., 2017). Lastly, (5) the dorsal cognitive circuit involved in executive functioning and cognitive flexibility, dysfunction in this circuit leads to rigid thinking and challenges in emotional regulation, thus exacerbating obsessions and repetitive behaviors.

Structural Brain Abnormalities

Structural abnormalities in individuals with OCD have been identified across a range of neuroimaging studies, revealing notable differences in several key brain regions. Generally, adolescents with OCD tend to exhibit a reduction in cortical thickness and volume, specifically in the parietal and frontal regions, such as the inferior and superior parietal cortices and certain frontal gyri (Pagliaccio et al., 2021; Wu et al., 2022). In contrast, the thalamus generally shows increased volume in these individuals, although the degree of enlargement and involvement of specific subnuclei seem to vary across studies (van den Heuvel et al., 2022).

Apart from global measurements, investigations into subcortical structures have uncovered distinct alterations that further delineate the neural landscape of OCD. Structural deviations in several subcortical regions including the caudate nucleus, putamen, and pallidum, are implicated in OCD pathology (Wang et al., 2022). Notably, Wang et al. (2022) identified specific structural changes in the nucleus accumbens (NAcc), amygdala, and pallidum among individuals diagnosed with OCD. Adolescents exhibited more pronounced structural deviations in the NAcc and pallidum than adults, with the NAcc being of particular interest due to its potential role as a biomarker for OCD development. Meanwhile in adults, amygdala alterations, characterized by inward deformation, correlated with symptom severity and highlighted the involvement of the fronto-limbic circuit, underscoring the role of fear and emotional dysregulation in OCD. These findings suggest that OCD is not only a disorder of habit formation (as CSTC emphasizes) but also involves dysfunctional emotional regulation and altered motivation systems.

These insights imply a developmental trajectory in OCD symptomatology; younger individuals may present more automatic, sensory-driven compulsions aligned with the sensorimotor circuit, whereas adults may experience heightened emotional dysregulation and cognitive rigidity indicative of fear-based compulsions within the fronto-limbic circuit (Wang et al., 2022).

Subjects are excluded from the study if they are currently taking common antidepressant or antipsychotic prescription medications because these drugs can significantly affect brain structure.

Informant Discrepancies

Traditionally, clinicians have depended on parents to provide comprehensive information about how an illness and its treatment affect their children. This reliance stems from the perception that children may not possess the cognitive and linguistic skills required to understand and respond to surveys accurately (Vygotsky, 1978). Consider the case of Liam, a 12-year-old having battled severe OCD for several years. After starting therapy, he was showing signs of improvement. According to Liam, he felt he was making excellent progress. He reduced his handwashing rituals from every hour to three times a day and started joining some family meals. He was also beginning to meet his friends for short walks around the neighborhood. However, his parents observed a different reality. While Liam had made some progress, he often became trapped in lengthy rituals that caused him significant distress. He had yet to return to school full-time, attending only partial days if he went at all. Though he started venturing out with friends, it was only to familiar, controlled environments. His parents continued to monitor his progress closely, supporting him in his journey while remaining aware of the continuous obstacles that his OCD presented. This vignette demonstrates the importance of recognizing that the child's perspective is distinct but equally valid. The insights provided by Liam can differ significantly from those of his mother, highlighting the potential discrepancies in information regardless of whether the goal is clinical assessment or research.

The phenomenon of informant discrepancy has been recognized for nearly 70 years, dating back to Lapouse and Monk's work in 1958. Achenbach, McConaughy, and Howell (1987) conducted a seminal analysis of 119 studies investigating these informant inconsistencies. Their key findings included: (a) reports of the same behavior by different informants generally show low to moderate agreement; (b) the reports of two informants observing children in the same setting are more similar than those of two informants observing children in different settings; (c) there is greater agreement between informants' reports for younger children compared to older ones; and (d) reports of externalizing behaviors like aggression show higher consistency than those of internalizing behaviors such as anxiety. They concluded by stating, "Different informants are needed for different situations. . . there is no royal road or preeminent gold standard for phenomena that are inevitably affected by assessment procedures and other situational variables" (p. 227–228). Consequently, the primary objectives of the informant discrepancies research summarized by Achenbach et al. (1987) were to outline the extent of informant discrepancies, identify the informant pairs (e.g., parent and child, teacher and parent) with the greatest discrepancies, and pinpoint the behavioral domains where these discrepancies were most pronounced. A prominent finding indicated discrepancies and varying accuracy in symptom reporting, with no clear consensus. Additionally important because obsessions (an internalizing symptom) are a distinguishing symptom of OCD.

The issue of informant discrepancies is particularly pertinent when interpreting study findings in the field of developmental psychopathology. A significant portion of the evidence about prevalence rates of psychological disorders, classification of diagnosis, and effectiveness of interventions for children is derived from reports by multiple informants (Weisz et al., 2005). For instance, the prevalence rates of conduct and oppositional defiant disorders in community samples can vary significantly depending on whether assessments are based solely on parental or teacher reports or if both sources are considered simultaneously. According to Offord et al. (1996), these rates range from 1.6% to 10.2%. More recent research by Munkvold et al. (2009) also noted substantial variability in oppositional defiant disorder prevalence, although the reported rates were lower, ranging from 0.2% to 2.6%. Furthermore, depending on the informant, it is typical to find inconsistent results from controlled studies evaluating psychological therapies (De Los Reyes & Kazdin, 2005).

While the use of multiple informants in mental health assessment is thought to enhance our understanding of the psychological functioning of children, particularly in the infant population, we are still in the process of discovering how to effectively utilize this wealth of information (Reyes, 2013).

Statistical Learning

The rapid growth of the bioinformatics field has led to an increasing reliance on machine learning techniques for the diagnosis and prediction of complex diseases based on their biomarkers.3 However, the high-dimensional nature of biomedical data, with a large number of variables but limited observation data, and multicollinearity, all could pose significant challenges. To address this, researchers have proposed and adopted various classification algorithms for bioinformatics4,5 including logistic regression, tree-based methods, and deep learning methods, which have emerged as powerful tools for capturing complex patterns across various domains, including image recognition678,9 and natural language processing1011.12 In this study, high correlations between neuroimaging features pose an important challenge and may lead to collinearity in predictive modeling. This study utilized a simulation environment mirroring imaging data from the ABCD study to examine the effectiveness of several supervised machine learning models. (Shen et al., 2024)  
In our investigation of various mainstream machine learning models, XGBoost emerged as the top performer across multiple challenging scenarios. Specifically, it demonstrated superior performance in handling multicollinearity, effectively managing predictors with non-linear relationships with the target variable, and addressing imbalanced data. XGBoost outperformed other mainstream classification method in the designed simulated data, which successfully captured all true signals hidden by the correlated features and thus have the highest AUC score. These findings underscore the versatility and robustness of XGBoost in navigating complex data structures and highlight its potential as a preferred choice for addressing real-world problems characterized by such challenges. (Shen et al., 2024)

Statistical Learning Theory (SLT) is the basis for many modern machine learning algorithms, emphasizing generalization by extracting patterns from data for accurate predictions (Luxburg & Schoelkopf, 2008). It is central to supervised learning, which uses labeled data to train models that relate predictor variables to a response variable, focusing on prediction accuracy rather than causal understanding (Shmueli, 2011). Predictive modeling prioritizes accuracy, using probabilistic or supervised learning models, and employs loss functions to measure prediction discrepancies and refine models for real-world use. In the context of clinical neuroscience and neuroimaging, the most common machine learning paradigm learns to associate brain imaging data with specific classifications such as diagnostic groups. This approach can help identify key predictive features that differentiate between these categories (Enrico et al., 2021).

Learning methods

Linear Model

Linear regressions provide a simple technique for analyzing data by assuming a linear relationship between input variables (X) and an output variable (Y) and typically estimates parameters using the least squares method. While effective for straightforward linear relationships, they are limited with complex data, which has led to advanced adaptations such as generalized linear models and support vector machines, offering broader applicability and improved modeling techniques for diverse patterns.

Decision Trees

A diagram of a family

AI-generated content may be incorrect.

***Figure 2.*** *Example of a decision tree used for predicting severity scores based on individual and socioeconomic factors. The root node begins with the condition Age ≥ 16. If this condition is met, the model predicts a severity score of 4. If the condition is not met, the decision process continues down to the next node. Each non-leaf node represents a decision based on a feature threshold, while the leaf nodes indicate the predicted severity score (Y). This hierarchical structure illustrates how different combinations of age, income, and education contribute to the final prediction.*

Decision trees provide a significant advancement to linear models by effectively handling non-linear relationships and interactions between variables. Tree models operate under the assumption that the interaction between the response variable and the predictors can be modeled through locally constant fits (Breiman, 2017). Unlike the simplicity of linear models, decision trees dynamically segment the feature space through recursive binary splits, adeptly addressing both classification and regression tasks (James et al., 2021). In classification tasks, this is achieved by creating subsets with a dominant output class, whereas in regression, it involves reducing the variability of target values within each subset. As illustrated in Figure 2. each node of the tree serves as a decision point, directing data further down branches or reaching leaf nodes where predictions are determined by metrics such as class majority or mean values. Thus, when used for regression the aim is to split the data into subsets that minimize the resulting mean squared error, mean absolute error, or the variance of the target variable within these subsets (Ryan, 2025). Although they are effective in capturing complex patterns, they are also prone to overfitting, which occurs when the model captures noise rather than the underlying pattern. Thus, it crucial to balance bias and variance for accuracy and generalizability.

Boosting

A diagram of a tree

AI-generated content may be incorrect.

***Figure 3.*** *Illustration of the boosting process used in ensemble learning methods. Training error decreases over successive iterations as additional decision trees are added. Initially, a single tree is trained, followed by subsequent trees that correct the errors of the previous ones. The ensemble prediction is formed by summing the outputs of multiple trees, leading to improved accuracy and reduced training error over time.*

Boosting, as illustrated in Figure 3, is an ensemble method used to enhance predictive accuracy (Schapire & Freund, 2012). An ensemble combines multiple models to make more accurate predictions than a single model. Boosting iteratively adds simpler models, like decision trees, that improve the overall fit by addressing errors from previous models. Figure 3 demonstrates how training error decreases as more trees are added, with the ensemble prediction formed by summing tree outputs for improved accuracy. Gradient Boosting, which operates similarly to gradient descent, optimizes individual trees to reduce error and minimizes the ensemble's collective error by correcting residuals with each added tree (Friedman, 2001). This approach allows diverse loss functions for error minimization, enhancing the alignment of predictions with true outcomes (Ryan, 2025). Adjusting observation weights helps the models focus on challenging cases, correcting errors while maintaining flexibility. XGBoost, or extreme gradient boosting, is a particularly efficient algorithm for fitting boosting models (Ren et al., 2019).

Tuning Parameters

When using XGBoost for regression tasks, several key parameters can be fine-tuned to optimize model performance (XGBoost Developers, 2022). It's important to note that this overview is not exhaustive of all tuning parameters available in XGBoost; rather, it is a short summary of some of the most impactful parameters to consider when optimizing regression models. The learning rate determines how quickly the model learns patterns, with smaller values allowing for more cautious learning to reduce overconfidence and potential overfitting. The maximum depth sets how complex each decision tree is by limiting the number of splits, with deeper trees capturing more intricate patterns but risking overfitting. “Minimum child weight” sets the amount of data required in a leaf node before further splitting, promoting simpler, less complex trees. For each tree, only a random subset of the predictor variables is made available to the model, and the size of this subset is a tuning parameter denoted colsample\_bytree in XGBoost. Furthermore, a threshold on the magnitude of improvement required for making a new split is controlled by the parameter “gamma”. Finally, only a random subset of the training data is used when fitting each tree, and the size of this subset is controlled by the parameter “subsample”. Together, these parameters help balance the model's ability to learn complex patterns with its ability to generalize well to new, unseen data.

In conclusion, the application of machine learning techniques, particularly XGBoost, offers a powerful methodology for modeling complex interactions between variables to predict an outcome of interest. This approach provides a robust framework for integrating diverse data types, such as neuroimaging, behavioral, and demographic variables. By using the collective strengths of multiple models, boosted ensembles surpass the predictive capabilities of single decision trees and linear models, effectively managing intricate relationships in high-dimensional data. This integration of computational tools with clinical insights holds promise for refining diagnostic criteria and enhancing personalized intervention strategies for OCD, paving the way for more precise and effective treatment approaches.

The present study

Study Design

Overview of the research framework.

Hypotheses regarding differences between clinical and healthy samples.

The present study strives to bridge the gap between neuroimaging advancements and the ongoing challenges posed by discrepancies in symptom reporting for adolescent OCD. While MRI studies provide insights into the neurobiological underpinnings of OCD, variations between parent and self-reports often result in inconsistencies in diagnosing and evaluating the disorder's severity, potentially impacting treatment efficacy. Notably, symptom reports of externalizing behaviors, such as compulsions, demonstrate greater consistency compared to internalizing behaviors like obsessions, underscoring the impact of information source on report reliability. To tackle these issues, this study explores the potential of structural brain data in predicting the severity of two higher-level OCD symptom domains—internalizing and externalizing—as reported by adolescents and their parents. Utilizing the XGBoost algorithm, the study aims to develop predictive models that capture the nuanced differences in symptom reporting. This research aims to deepen our understanding of how neuroimaging data can enhance symptom assessments in adolescent OCD, ultimately contributing to improved personalized treatment outcomes.

Research question

Can structural brain data be used to predict the level of OCD symptoms reported by youths and parents?

Supplementary questions:

Is the predictive accuracy of structural brain data for internalizing domain higher for self-reported symptoms than for parent-reported symptoms?

Is the predictive accuracy of structural brain data for externalizing domain higher for parent-reported symptoms than for self-reported symptoms?

Methods

Data Source and Acquisition

The Adolescent Brain and Cognitive Development (ABCD) Study is a comprehensive decade-long research initiative in the United States (US) designed to enhance our understanding of physical and mental health and risk factors during adolescence. The study tracks children from ages 9-10 through late adolescence and into early adulthood. This age range includes a crucial developmental stage, when exposure to substance use, and the start of several mental health conditions take place. The repository includes around 12,000 children at baseline, recruited from 21 research sites (Karcher & Barch, 2021). To ensure the cohort is diverse and representative, the ABCD study employs a multi-stage probability sampling technique to minimize selection bias, thus increasing the generalizability of the findings (Garavan et al., 2018). The ABCD comprises a wide range of behavioral (Barch et al., 2018), multimodal brain imaging (Casey et al., 2018), and other evaluations (Zucker et al., 2018). It conducts annual lab-based evaluations and biannual imaging scans to assess mental and physical health metrics (Saragosa-Harris et al., 2022). The data utilized in this thesis is sourced from the ABCD Data Release 5.1 (Haist & Jernigan, 2023). To ensure consistency in data analysis, this thesis utilizes only the year two follow-up time point, as it provided the most comprehensive available data across all key variables of interest, including, neuroimaging data and questionnaire responses.

REK stuff hereeeee

Structural MRI

The ABCD study collects MRI data from three different scanner platforms located at 21 collection sites across the US: Siemens Prisma, General Electric 750, and Philips scanners (Casey et al., 2018). T1-weighted (T1w) imagesare acquired using a 3D T1w inversion-prepared RF-spoiled gradient echo sequence with 1 mm isotropic resolution (Casey et al., 2018). Prospective motion correction is applied when available (currently only on Siemens and GE scanners; (Tisdall et al., 2012; White et al., 2010)). The acquisition parameters across scanner platforms are displayed in Table X.

The ABCD MRI acquisition protocol utilizes high-density phased array head coils, which can lead to significant variations in image intensity. Additionally, head motion poses a considerable challenge, particularly for a pediatric population, as it can degrade image quality and distort the resulting metrics (Reuter et al., 2015; Satterthwaite et al., 2012). Therefore, although prospective motion correction techniques are implemented to mitigate the effects of motion in structural MRI scans, excessive head movement can still introduce substantial artefacts, hindering accurate brain segmentation (Tisdall et al., 2016). If these discrepancies are not adequately addressed, they may lead to inaccuracies in cortical surface reconstruction and brain segmentation (ref).

Due to the potential artifacts in MRI images, T1w quality control during the MRI acquisition includes three checks. Firstly, (1) automated checks for protocol compliance assess the completeness of the imaging series and ensure that they meet the specified parameters; these criteria include verifying whether key imaging characteristics such as voxel size and repetition time align with the expected values for each scanner. (2) Automated quality control procedures involve calculating signal-to-noise ratio and head motion statistics. Lastly, this is complemented by (3) a manual quality control process where trained technicians visually assess image quality, identifying and flagging significant artefacts. Series that fail to meet quality standards are excluded from further processing and analysis, and reviewers are required to document observable artefacts using standardized notations.

Preprocessing sMRI

The image processing pipeline, as depicted in Figure X, involves several systematic steps to ensure the accuracy and reliability of the MRI data. The preprocessing steps recommended by ABCD include (1) Correction for Gradient Nonlinearity Distortions, which addresses distortions in the MRI images introduced by the scanner's gradient system (Jovicich et al., 2006; Wald et al., 2001). These corrections are specific to each scanner model and are provided by MRI manufacturers to enhance image fidelity. (2) Bias Field Correction involves correcting brightness variations across the brain images, a phenomenon known as intensity non-uniformity. This distortion is often caused by the proximity of brain tissue to the MRI coils, leading to areas with extremely high-intensity values that may be erroneously identified as non-brain tissue (i.e., skull). To address this issue, T2-w images are registered to T1-w images using a technique called mutual information, which facilitates accurate alignment and overlay of the different scan types (Wells et al., 1996). Following this registration, the procedure includes tissue segmentation and the application of smoothly varying estimated B1-bias fields to adjust brightness levels, ensuring that each tissue type is represented consistently across the images (Sled et al., 1998). Lastly, (3) Resample to Isotropic: The final image preprocessing step standardizes the viewing and analysis of brain structures. The images are resized and aligned with an internally generated reference brain that features isotropic voxels of 1.0 mm and is approximately aligned with the anterior commissure/posterior commissure (AC/PC) axis (Friston et al., 1995).

Brain Segmentation

Cortical surface reconstruction and subcortical segmentation are conducted using FreeSurfer version 7.1.1 (https://surfer.nmr.mgh.harvard.edu). FreeSurfer has been validated in adolescent samples (Biffen et al., 2020). The process begins with skull-stripping, which removes the skull and non-brain tissues from the MRI images (Ségonne et al., 2004). Simultaneously, white matter segmentation is conducted to identify white matter regions, while initial mesh creation produces a preliminary three-dimensional representation of the brain's surface (Dale et al., 1999). Following this, the correction of topological defects on the surface model is applied to address errors or irregularities (Fischl et al., 2001; Segonne et al., 2007). The surface model is optimized and refined (Dale et al., 1999; Dale & Sereno, 1993; Fischl & Dale, 2000). Lastly, the reconstructed brain surface undergoes nonlinear registration to a spherical atlas, aligning it with a standardized spherical model to facilitate consistent comparisons across different subjects (Fischl et al., 1999).

Regions of Interest

After completing cortical reconstruction, specific brain regions are labelled by two atlases. Cortical areas are labeled using the Destrieux atlas-based classification (Destrieux et al., 2010). It is widely used in structural MRI studies to analyze cortical volume in neurodevelopmental research ref. This atlas uses a sulco-gyral classification, distinguishing between exposed gyri and buried sulci based on mean curvature and convexity, thus providing 74 bilateral regions (148 total). Subcortical structures were analyzed using the Automated Segmentation of the Subcortical Structures (ASEG) provided by FreeSurfer (Fischl et al., 2002). This atlas allows the segmentation and volume measurement of subcortical areas and other intracranial structures, providing 46 regions in total. Combining these atlases facilitates a comprehensive analysis of cortical and subcortical regions. Once both cortical and subcortical structures are labelled, we obtain 194 parcellated brain volumes per individual, presented in a tabulated format.

Demographics and categorical diagnosis

The Kiddie Schedule for Affective Disorders and Schizophrenia (KSADS-5 2.0) is a comprehensive diagnostic tool compatible with the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) criteria, supporting the categorical approach to psychiatric diagnoses (Kobak et al., 2013) (APA, 2000). This approach uses established criteria and diagnoses may be classified as "certain," "possible," "in remission," or "not present." Demographic questions, including age, sex, race, and ethnicity, are also retrieved from the KSADS-5.

Self and Parental Reports of dimensional diagnosis

The Achenbach System of Empirically Based Assessment (ASEBA) is a comprehensive evaluation tool developed after years of research and practical use (*ASEBA*, 2019). It is designed to assess behavioral, emotional, and social aspects, along with strengths, competencies, and adaptive functioning in individuals ranging from 1½ years old to over 90. ASEBA is widely applied in diverse areas such as mental health services, education, healthcare, research, and more. The Child Behavior Checklist (CBCL) and Brief Problem Monitor (BPM), two components of the ASEBA, provides a dimensional diagnostic/assessment approach that places behaviors along a continuum of frequency and/or severity. Raw scores from these instruments are converted into standardized scores using ASEBA-defined algorithms, which account for informant type, age, sex, and ethnicity. These normed scores are expressed as T-scores, with a mean of 50 and a standard deviation of 10.

Parent-Reported Child Behavior Checklist

The CBCL is a component of the ASEBA first published in 2001, and is used to assess children's behavioral, emotional, or social problems (Achenbach, 2001). It is a 112-item parent-reported survey, which uses a 3-point Likert scale for responses: "Very True," "Somewhat True," or "Not True," where parents are asked to rate each item based on their child's behavior "now or within the past six months." As depicted in Figure 5, the CBCL consists of several dimensions categorized into Syndrome Scales and DSM-Oriented Scales. The eight syndrome scales are established through factor analysis. They encompass clusters of common behaviors or symptoms. Meanwhile, the more recently developed seven DSM-Oriented Scales align with diagnostic categories outlined in the DSM-5 (American Psychiatric Association, 2013; Nelson et al., 2001). Furthermore, these scales are grouped into three high-level domains Internalizing, Externalizing, and Total Problems scales. These dimensions offer a detailed assessment of a child's emotional, social, and behavioral functioning, aiding in identifying areas that may benefit from therapeutic or educational interventions.

Self-Reported Brief Problem Monitor

The BPM, another component of the ASEBA, was first published in 2011 (Achenbach et al., 2011). Developed to complement parental assessments, adolescents provide self-reports on higher-level domains and attention. It is a 19-item self-reported survey used to assess children's behavioral and emotional functioning and their responses to interventions (RTIs). It also uses a 3-point Likert scale for responses: "Very True", "Somewhat True," or "Not True." Children are instructed to rate each item based on their behavior "currently or within the past six months." As illustrated in Figure 5, the BPM measures four scales, including Internalizing, Attention Problems, Externalizing, and Total Problems scales, paralleling the items and scales found on the more comprehensive CBCL/6-18 (Achenbach et al., 2017).



***Figure 5.*** *The structure of the ASEBA specifically focuses on the CBCL and the BPM. The parent-reported CBCL consists of Syndrome Scales and the more recently developed DSM-Oriented Scales. The DSM-oriented scales are aligned with diagnostic criteria from the DSM and include categories such as OCD and Anxiety Problems. The syndrome scales include clusters of symptoms, which are further grouped into three high-level domains known as (1) Internalizing Problems, (2) Externalizing, and (3) Total Problems score that sums all problem items. The child-reported BPM is a shorter version that provides a rapid assessment parallel to dimensions in CBCL for monitoring behavioral and emotional functioning over time.*

Several criteria were applied for exclusion from the study, illustrated in Figure 4. Subjects were excluded if they lack usable imaging data or if there are missing reports from either parents or children regarding internalizing and/or externalizing behaviors. Furthermore, subjects currently using antidepressant or antipsychotic medications were excluded (list of meds?) as these drugs can significantly affect brain structure. Healthy control subjects were defined as subjects who did not meet diagnostic criteria for any present or current psychiatric disorder as assessed by the KSADS-5. A total of 6,261 participants were included in the study.



***Figure 4.*** *Flowchart of participant selection and subgroup classification at 2-year follow-up.*

For the healthy control group (n = 5,869), the mean age of participants was 9.48 years (SD = 0.51). The sex distribution included 47.5% female (n = 2,790), 0% identified as intersex-male (n = 1), and 52.4% male (n = 3,078). The racial and ethnic composition of the group was as follows: 2.2% Asian (n = 131), 13.3% Black (n = 778), 19% Hispanic (n = 1,114), 9.8% identifying as Other (n = 574), and 55.8% White (n = 3,272). For the OCD group (n = 392), the mean age of participants was 9.46 years (SD = 0.5). The sex distribution included 47.7% female (n = 187) and 52.3% male (n = 205). The racial and ethnic composition was 1% Asian (n = 4), 15.1% Black (n = 59), 19.6% Hispanic (n = 77), 14.5% identifying as Other (n = 57), and 49.7% White (n = 195).

Modelling approach

All analysis and data handling was done in R version 4.3.3. We built four extreme gradient boosting models using XGBoost 3.0 from the xgboost package. A separate model was made for each symptom domain, resulting in four distinct prediction models:

1. Parent-reported internalizing score
2. Parent-reported externalizing score
3. Child-reported internalizing score
4. Child-reported externalizing score

Each model used a set of 194 predictor variables derived from the Destrieux and ASEG brain regions. It is important to note that the target variable was excluded from the predictor set to avoid bias in the predictions. For handling missing data, we performed mean imputation for several brain regions, specifically the cortical volumes in mm³ for the left hemisphere Destrieux regions: sulcus intermedius primus (NA=4), transverse temporal sulcus (NA=1), and total (NA=5), and for the right hemisphere Destrieux regions: sulcus intermedius primus (NA=1), transverse temporal sulcus (NA=1), and total (NA=2), along with the overall Destrieux total (NA=7). Additionally, we excluded two variables—the ASEG ROI right lesion volume and the ASEG ROI left(?) lesion volume—because over 30% of the data was missing. Target variables were standardized using z-score transformation to enable clear comparisons across the datasets. The dataset was then partitioned into training and testing subsets, with 80% of the data (n= 5009) allocated for training and the remaining 20% (n=1252) reserved for testing.

Training

This process involved exploring several parameters, including number of boosting rounds, tree depth, learning rate, and subsampling ratios. We optimized model selection by minimizing the root-mean-square error (RMSE), which ensured high predictive accuracy. The cross-validation (CV) results were visualized through plots that illustrated the interaction between boosting rounds and CV errors across varying tree depths and learning rates. These plots elucidate how model complexity and iterations influenced performance. Due to high class imbalance, we explored a range of subsample parameters. We noted that our subsamples exhibited significant discrepancies in class distribution, which informed our approach to balancing the datasets.

Testing

Once the optimal hyperparameters are identified, we evaluated the feature importance for each model. Feature importance plots were created to identify the most influential predictors of symptom severity. Predictions were then generated using the trained model. Feature Importance Analysis: Using the results from the trained model, we conducted a feature importance analysis. This analysis identified the relative significance of each feature, which we displayed graphically, highlighting the top three features that significantly impacted our model's predictions. This methodological approach is crucial for both evaluating predictive accuracy and understanding the key variables that influence the model's decision-making processes. Model performance evaluations: Apart from the RMSE, we also calculated several performance metrics, including R-squared (R²) and mean absolute error (MAE), using the caret package. This involved comparing the predictions generated by the model against the actual outcomes to assess the model’s ability to generalize to unseen data. To further assess our results, we conducted a permutation spread analysis, comparing the null models against our trained models as a way to validate our findings.

Results

Discussion

References

Achenbach, McConaughy, S., Ivanova, M., & Rescorla, L. (2017). Manual for the aseba brief problem monitor for ages 6–18 (bpm/6–18). *Burlington: University of Vermont Research Center for Children, Youth, and Families*.

Achenbach, T. M. (2001). *Manual for the ASEBA school-age forms & profiles: Child behavior checklist for ages 6-18, teacher’s report form, youth self-report: An integrated system of multi-informant assessment*. ASEBA.

Achenbach, T. M. (2009). *The Achenbach system of empirically based assessment (ASEBA): Development, findings, theory, and applications*. University of Vermont, Research Center for Children, Youth, & Families.

Achenbach, T. M., McConaughy, S. H., Ivanova, M. Y., & Rescorla, L. A. (2011). Manual for the ASEBA brief problem monitor (BPM). *Burlington, VT: ASEBA*, *33*.

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders: DSM-5* (5th ed.). American Psychiatric Association.

*ASEBA*. (2019, January 14). https://aseba.org/aseba-overview/

Barch, D. M., Albaugh, M. D., Avenevoli, S., Chang, L., Clark, D. B., Glantz, M. D., Hudziak, J. J., Jernigan, T. L., Tapert, S. F., Yurgelun-Todd, D., Alia-Klein, N., Potter, A. S., Paulus, M. P., Prouty, D., Zucker, R. A., & Sher, K. J. (2018). Demographic, physical and mental health assessments in the adolescent brain and cognitive development study: Rationale and description. *Dev Cogn Neurosci*, *32*, 55–66. https://doi.org/10.1016/j.dcn.2017.10.010

Biffen, S. C., Warton, C. M. R., Dodge, N. C., Molteno, C. D., Jacobson, J. L., Jacobson, S. W., & Meintjes, E. M. (2020). Validity of automated FreeSurfer segmentation compared to manual tracing in detecting prenatal alcohol exposure-related subcortical and corpus callosal alterations in 9- to 11-year-old children. *NeuroImage : Clinical*, *28*, 102368. https://doi.org/10.1016/j.nicl.2020.102368

Bragdon, L. B., & Coles, M. E. (2017). Examining Heterogeneity of Obsessive-Compulsive Disorder: Evidence for Subgroups Based on Motivations. *J Anxiety Disord*, *45*, 64–71. https://doi.org/10.1016/j.janxdis.2016.12.002

Breiman, L. (2017). *Classification and Regression Trees*. Routledge. https://doi.org/10.1201/9781315139470

Brennan, B. P., & Rauch, S. L. (2017). Functional Neuroimaging Studies in Obsessive-Compulsive Disorder: Overview and Synthesis. In C. Pittenger & C. Pittenger (Eds.), *Obsessive-compulsive Disorder: Phenomenology, Pathophysiology, and Treatment* (p. 0). Oxford University Press. https://doi.org/10.1093/med/9780190228163.003.0021

Casey, B. j., Jones, R. M., & Hare, T. A. (2008). The Adolescent Brain. *Annals of the New York Academy of Sciences*, *1124*(1), 111–126. https://doi.org/10.1196/annals.1440.010

Casey, Cannonier, T., Conley, M. I., Cohen, A. O., Barch, D. M., Heitzeg, M. M., Soules, M. E., Teslovich, T., Dellarco, D. V., Garavan, H., Orr, C. A., Wager, T. D., Banich, M. T., Speer, N. K., Sutherland, M. T., Riedel, M. C., Dick, A. S., Bjork, J. M., Thomas, K. M., … ABCD Imaging Acquisition Workgroup. (2018). The Adolescent Brain Cognitive Development (ABCD) study: Imaging acquisition across 21 sites. *Developmental Cognitive Neuroscience*, *32*, 43–54. https://doi.org/10.1016/j.dcn.2018.03.001

Cyr, M., Pagliaccio, D., Yanes-Lukin, P., Goldberg, P., Fontaine, M., Rynn, M. A., & Marsh, R. (2021). Altered fronto-amygdalar functional connectivity predicts response to cognitive behavioral therapy in pediatric obsessive-compulsive disorder. *Depression and Anxiety*, *38*(8), 836–845. https://doi.org/10.1002/da.23187

Dale, A. M., Fischl, B., & Sereno, M. I. (1999). Cortical Surface-Based Analysis: I. Segmentation and Surface Reconstruction. *Neuroimage*, *9*(2), 179–194. https://doi.org/10.1006/nimg.1998.0395

Dale, A. M., & Sereno, M. I. (1993). Improved Localizadon of Cortical Activity by Combining EEG and MEG with MRI Cortical Surface Reconstruction: A Linear Approach. *J Cogn Neurosci*, *5*(2), 162–176. https://doi.org/10.1162/jocn.1993.5.2.162

De Los Reyes, A., & Kazdin, A. E. (2005). Informant Discrepancies in the Assessment of Childhood Psychopathology: A Critical Review, Theoretical Framework, and Recommendations for Further Study. *Psychological Bulletin*, *131*(4), 483–509. https://doi.org/10.1037/0033-2909.131.4.483

de Mathis, M. A., Diniz, J. B., Hounie, A. G., Shavitt, R. G., Fossaluza, V., Ferrão, Y., Leckman, J. F., de Bragança Pereira, C., do Rosario, M. C., & Miguel, E. C. (2013). Trajectory in obsessive-compulsive disorder comorbidities. *Eur Neuropsychopharmacol*, *23*(7), 594–601. https://doi.org/10.1016/j.euroneuro.2012.08.006

de Wit, S. J., Alonso, P., Schweren, L., Mataix-Cols, D., Lochner, C., Menchón, J. M., Stein, D. J., Fouche, J.-P., Soriano-Mas, C., Sato, J. R., Hoexter, M. Q., Denys, D., Nakamae, T., Nishida, S., Kwon, J. S., Jang, J. H., Busatto, G. F., Cardoner, N., Cath, D. C., … van den Heuvel, O. A. (2014). Multicenter Voxel-Based Morphometry Mega-Analysis of Structural Brain Scans in Obsessive-Compulsive Disorder. *American Journal of Psychiatry*, *171*(3), 340–349. https://doi.org/10.1176/appi.ajp.2013.13040574

Destrieux, C., Fischl, B., Dale, A., & Halgren, E. (2010). Automatic parcellation of human cortical gyri and sulci using standard anatomical nomenclature. *NeuroImage*, *53*(1), 1–15. https://doi.org/10.1016/j.neuroimage.2010.06.010

Enrico, P., Delvecchio, G., Turtulici, N., Pigoni, A., Villa, F. M., Perlini, C., Rossetti, M. G., Bellani, M., Lasalvia, A., Bonetto, C., Scocco, P., D’Agostino, A., Torresani, S., Imbesi, M., Bellini, F., Veronese, A., Bocchio-Chiavetto, L., Gennarelli, M., Balestrieri, M., … Brambilla, P. (2021). Classification of Psychoses Based on Immunological Features: A Machine Learning Study in a Large Cohort of First-Episode and Chronic Patients. *Schizophrenia Bulletin*, *47*(4), 1141–1155. https://doi.org/10.1093/schbul/sbaa190

Fischl, B., & Dale, A. M. (2000). Measuring the Thickness of the Human Cerebral Cortex from Magnetic Resonance Images. *Proc Natl Acad Sci U S A*, *97*(20), 11050–11055. https://doi.org/10.1073/pnas.200033797

Fischl, B., Liu, A., & Dale, A. M. (2001). Automated manifold surgery: Constructing geometrically accurate and topologically correct models of the human cerebral cortex. *IEEE Trans Med Imaging*, *20*(1), 70–80. https://doi.org/10.1109/42.906426

Fischl, B., Salat, D. H., Busa, E., Albert, M., Dieterich, M., Haselgrove, C., van der Kouwe, A., Killiany, R., Kennedy, D., Klaveness, S., Montillo, A., Makris, N., Rosen, B., & Dale, A. M. (2002). Whole brain segmentation: Automated labeling of neuroanatomical structures in the human brain. *Neuron*, *33*(3), 341–355. https://doi.org/10.1016/s0896-6273(02)00569-x

Fischl, B., Sereno, M. I., Tootell, R. B. H., & Dale, A. M. (1999). High-resolution intersubject averaging and a coordinate system for the cortical surface. *Hum. Brain Mapp*, *8*(4), 272–284.

Friedman, J. H. (2001). Greedy Function Approximation: A Gradient Boosting Machine. *The Annals of Statistics*, *29*(5), 1189–1232.

Friston, Karl. J., Ashburner, J., Frith, C. D., Poline, J.-B., Heather, J. D., & Frackowiak, R. S. J. (1995). Spatial registration and normalization of images. *Hum. Brain Mapp*, *3*(3), 165–189. https://doi.org/10.1002/hbm.460030303

Garavan, H., Bartsch, H., Conway, K., Decastro, A., Goldstein, R. Z., Heeringa, S., Jernigan, T., Potter, A., Thompson, W., & Zahs, D. (2018). Recruiting the ABCD sample: Design considerations and procedures. *Developmental Cognitive Neuroscience*, *32*, 16–22. https://doi.org/10.1016/j.dcn.2018.04.004

Graybiel, A. M., & Rauch, S. L. (2000). Toward a Neurobiology of Obsessive-Compulsive Disorder. *Neuron*, *28*(2), 343–347. https://doi.org/10.1016/S0896-6273(00)00113-6

Guzick, A. G., Cooke, D. L., McNamara, J. P. H., Reid, A. M., Graziano, P. A., Lewin, A. B., Murphy, T. K., Goodman, W. K., Storch, E. A., & Geffken, G. R. (2019). Parents’ Perceptions of Internalizing and Externalizing Features in Childhood OCD. *Child Psychiatry Hum Dev*, *50*(4), 692–701. https://doi.org/10.1007/s10578-019-00873-w

Haist, F., & Jernigan, T. L. (2023). *Adolescent Brain Cognitive Development Study (ABCD)—Annual Release 5.1*. https://doi.org/10.15154/Z563-ZD24

Hu, X., Du, M., Chen, L., Li, L., Zhou, M., Zhang, L., Liu, Q., Lu, L., Mreedha, K., Huang, X., & Gong, Q. (2017). Meta-analytic investigations of common and distinct grey matter alterations in youths and adults with obsessive-compulsive disorder. *Neuroscience & Biobehavioral Reviews*, *78*, 91–103. https://doi.org/10.1016/j.neubiorev.2017.04.012

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2021). *An Introduction to Statistical Learning: With Applications in R*. Springer US. https://doi.org/10.1007/978-1-0716-1418-1

Jovicich, J., Czanner, S., Greve, D., Haley, E., van der Kouwe, A., Gollub, R., Kennedy, D., Schmitt, F., Brown, G., MacFall, J., Fischl, B., & Dale, A. (2006). Reliability in multi-site structural MRI studies: Effects of gradient non-linearity correction on phantom and human data. *NeuroImage*, *30*(2), 436–443. https://doi.org/10.1016/j.neuroimage.2005.09.046

Karcher, N. R., & Barch, D. M. (2021). The ABCD study: Understanding the development of risk for mental and physical health outcomes. *Neuropsychopharmacology*, *46*(1), 131–142. https://doi.org/10.1038/s41386-020-0736-6

Kessler, R. C., Ormel, J., Petukhova, M., McLaughlin, K. A., Green, J. G., Russo, L. J., Stein, D. J., Zaslavsky, A. M., Aguilar-Gaxiola, S., Alonso, J., Andrade, L., Benjet, C., de Girolamo, G., de Graaf, R., Demyttenaere, K., Fayyad, J., Haro, J. M., Hu, C. yi, Karam, A., … Üstün, T. B. (2011). Development of Lifetime Comorbidity in the World Health Organization World Mental Health Surveys. *Arch Gen Psychiatry*, *68*(1), 90–100. https://doi.org/10.1001/archgenpsychiatry.2010.180

Kobak, K. A., Kratochvil, C., Stanger, C., & Kaufman, J. (2013). Computerized screening of comorbidity in adolescents with substance or psychiatric disorders. *Anxiety Disorders and Depression.(La Jolaa, CA)*.

Luxburg, U. von, & Schoelkopf, B. (2008). *Statistical Learning Theory: Models, Concepts, and Results* (No. arXiv:0810.4752). arXiv. https://doi.org/10.48550/arXiv.0810.4752

Munkvold, L., Lundervold, A., Lie, S. A., & Manger, T. (2009). Should there be separate parent and teacher-based categories of ODD? Evidence from a general population. *J Child Psychol Psychiatry*, *50*(10), 1264–1272. https://doi.org/10.1111/j.1469-7610.2009.02091.x

Nazeer, A., Latif, F., Mondal, A., Azeem, M. W., & Greydanus, D. E. (2020). Obsessive-compulsive disorder in children and adolescents: Epidemiology, diagnosis and management. *Translational Pediatrics*, *9*(Suppl 1), S76.

Nelson, E. C., Hanna, G. L., Hudziak, J. J., Botteron, K. N., Heath, A. C., & Todd, R. D. (2001). Obsessive-Compulsive Scale of the Child Behavior Checklist: Specificity, Sensitivity, and Predictive Power. *Pediatrics*, *108*(1), e14–e14. https://doi.org/10.1542/peds.108.1.e14

Offord, D. R., Boyle, M. H., Racine, Y., Szatmari, P., Fleming, J. E., Sanford, M., & Lipman, E. L. (1996). Integrating Assessment Data from Multiple Informants. *Journal of the American Academy of Child & Adolescent Psychiatry*, *35*(8), 1078–1085. https://doi.org/10.1097/00004583-199608000-00019

Pagliaccio, D., Durham, K., Fitzgerald, K. D., & Marsh, R. (2021). Obsessive-Compulsive Symptoms Among Children in the Adolescent Brain and Cognitive Development Study: Clinical, Cognitive, and Brain Connectivity Correlates. *Biol Psychiatry Cogn Neurosci Neuroimaging*, *6*(4), 399–409. https://doi.org/10.1016/j.bpsc.2020.10.019

Picó-Pérez, M., Moreira, P. S., de Melo Ferreira, V., Radua, J., Mataix-Cols, D., Sousa, N., Soriano-Mas, C., & Morgado, P. (2020). Modality-specific overlaps in brain structure and function in obsessive-compulsive disorder: Multimodal meta-analysis of case-control MRI studies. *Neuroscience & Biobehavioral Reviews*, *112*, 83–94. https://doi.org/10.1016/j.neubiorev.2020.01.033

Ren, H., Wang, X., Wang, S., & Zhang, Z. (2019). Predict Fluid Intelligence of Adolescent Using Ensemble Learning. In K. M. Pohl, W. K. Thompson, E. Adeli, & M. G. Linguraru (Eds.), *Adolescent Brain Cognitive Development Neurocognitive Prediction* (pp. 66–73). Springer International Publishing.

Reuter, M., Tisdall, M. D., Qureshi, A., Buckner, R. L., van der Kouwe, A. J. W., & Fischl, B. (2015). Head motion during MRI acquisition reduces gray matter volume and thickness estimates. *Neuroimage*, *107*, 107–115. https://doi.org/10.1016/j.neuroimage.2014.12.006

Reyes, A. D. L. (2013). Strategic objectives for improving understanding of informant discrepancies in developmental psychopathology research. *Development and Psychopathology*, *25*(3), 669–682. https://doi.org/10.1017/S0954579413000096

Ryan, M. (2025). *Machine Learning for Tabular Data.* (1st ed.). Manning Publications Co. LLC.

Saragosa-Harris, N. M., Chaku, N., MacSweeney, N., Guazzelli Williamson, V., Scheuplein, M., Feola, B., Cardenas-Iniguez, C., Demir-Lira, E., McNeilly, E. A., Huffman, L. G., Whitmore, L., Michalska, K. J., Damme, K. S., Rakesh, D., & Mills, K. L. (2022). A practical guide for researchers and reviewers using the ABCD Study and other large longitudinal datasets. *Developmental Cognitive Neuroscience*, *55*, 101115. https://doi.org/10.1016/j.dcn.2022.101115

Satterthwaite, T. D., Wolf, D. H., Loughead, J., Ruparel, K., Elliott, M. A., Hakonarson, H., Gur, R. C., & Gur, R. E. (2012). Impact of in-scanner head motion on multiple measures of functional connectivity: Relevance for studies of neurodevelopment in youth. *Neuroimage*, *60*(1), 623–632. https://doi.org/10.1016/j.neuroimage.2011.12.063

Schapire, R. E., & Freund, Y. (2012). *Boosting: Foundations and Algorithms*. The MIT Press. https://doi.org/10.7551/mitpress/8291.001.0001

Ségonne, F., Dale, A. M., Busa, E., Glessner, M., Salat, D., Hahn, H. K., & Fischl, B. (2004). A hybrid approach to the skull stripping problem in MRI. *Neuroimage*, *22*(3), 1060–1075. https://doi.org/10.1016/s1053-8119(04)00188-0

Segonne, F., Pacheco, J., & Fischl, B. (2007). Geometrically Accurate Topology-Correction of Cortical Surfaces Using Nonseparating Loops. *IEEE Trans Med Imaging*, *26*(4), 518–529. https://doi.org/10.1109/TMI.2006.887364

Shen, X., Zhang, Q., Zheng, H., & Qi, W. (2024). *Harnessing XGBoost for Robust Biomarker Selection of Obsessive-Compulsive Disorder (OCD) from Adolescent Brain Cognitive Development (ABCD) data* (No. arXiv:2407.00028). arXiv. https://doi.org/10.48550/arXiv.2407.00028

Shephard, E., Stern, E. R., van den Heuvel, O. A., Costa, D. L. C., Batistuzzo, M. C., Godoy, P. B. G., Lopes, A. C., Brunoni, A. R., Hoexter, M. Q., Shavitt, R. G., Reddy, Y. C. J., Lochner, C., Stein, D. J., Simpson, H. B., & Miguel, E. C. (2021). Toward a neurocircuit-based taxonomy to guide treatment of obsessive–compulsive disorder. *Mol Psychiatry*, *26*(9), 4583–4604. https://doi.org/10.1038/s41380-020-01007-8

Shmueli, G. (2011, January 5). *To Explain or to Predict?* arXiv.Org. https://doi.org/10.1214/10-STS330

Slade, T., & Watson, D. (2006). The structure of common DSM-IV and ICD-10 mental disorders in the Australian general population. *Psychol. Med*, *36*(11), 1593–1600. https://doi.org/10.1017/S0033291706008452

Sled, J. G., Zijdenbos, A. P., & Evans, A. C. (1998). A nonparametric method for automatic correction of intensity nonuniformity in MRI data. *IEEE Trans Med Imaging*, *17*(1), 87–97. https://doi.org/10.1109/42.668698

Stern, E. R., Collins, K. A., Bragdon, L. B., Eng, G. K., Recchia, N., Coffey, B. J., Leibu, E., Murrough, J. W., Tobe, R. H., Iosifescu, D. V., Burdick, K. E., & Goodman, W. K. (2025). Randomized Controlled Trial of the Effects of High-Dose Ondansetron on Clinical Symptoms and Brain Connectivity in Obsessive-Compulsive and Tic Disorders. *American Journal of Psychiatry*, *182*(3), 285–296. https://doi.org/10.1176/appi.ajp.20240294

Tisdall, M. D., Hess, A. T., Reuter, M., Meintjes, E. M., Fischl, B., & van der Kouwe, A. J. W. (2012). Volumetric navigators for prospective motion correction and selective reacquisition in neuroanatomical MRI. *Magnetic Resonance Medicine*, *68*(2), 389–399. https://doi.org/10.1002/mrm.23228

Tisdall, M. D., Reuter, M., Qureshi, A., Buckner, R. L., Fischl, B., & van der Kouwe, A. J. W. (2016). Prospective motion correction with volumetric navigators (vNavs) reduces the bias and variance in brain morphometry induced by subject motion. *Neuroimage*, *127*, 11–22. https://doi.org/10.1016/j.neuroimage.2015.11.054

van den Heuvel, O. A., Boedhoe, P. S. W., Bertolin, S., Bruin, W. B., Francks, C., Ivanov, I., Jahanshad, N., Kong, X.-Z., Kwon, J. S., O’Neill, J., Paus, T., Patel, Y., Piras, F., Schmaal, L., Soriano-Mas, C., Spalletta, G., van Wingen, G. A., Yun, J.-Y., Vriend, C., … ENIGMA-OCD working group. (2022). An overview of the first 5 years of the ENIGMA obsessive-compulsive disorder working group: The power of worldwide collaboration. *Human Brain Mapping*, *43*(1), 23–36. https://doi.org/10.1002/hbm.24972

van den Heuvel, O. A., Remijnse, P. L., Mataix-Cols, D., Vrenken, H., Groenewegen, H. J., Uylings, H. B. M., van Balkom, A. J. L. M., & Veltman, D. J. (2009). The major symptom dimensions of obsessive-compulsive disorder are mediated by partially distinct neural systems. *Brain: A Journal of Neurology*, *132*(Pt 4), 853–868. https://doi.org/10.1093/brain/awn267

van den Heuvel, O. A., van Wingen, G., Soriano-Mas, C., Alonso, P., Chamberlain, S. R., Nakamae, T., Denys, D., Goudriaan, A. E., & Veltman, D. J. (2016). Brain circuitry of compulsivity. *European Neuropsychopharmacology: The Journal of the European College of Neuropsychopharmacology*, *26*(5), 810–827. https://doi.org/10.1016/j.euroneuro.2015.12.005

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes* (Vol. 86). Harvard university press.

Wald, L., Schmitt, F., & Dale, A. (2001). Systematic spatial distortion in MRI due to gradient non-linearities. *NeuroImage (Orlando, Fla.)*, *13*(6), 50–50. https://doi.org/10.1016/S1053-8119(01)91393-X

Wang, Z., Fontaine, M., Cyr, M., Rynn, M. A., Simpson, H. B., Marsh, R., & Pagliaccio, D. (2022). Subcortical shape in pediatric and adult obsessive-compulsive disorder. *Depression and Anxiety*, *39*(6), 504–514. https://doi.org/10.1002/da.23261

Weisz, J. R., Doss, A. J., & Hawley, K. M. (2005). Youth Psychotherapy Outcome Research: A Review and Critique of the Evidence Base. *Annual Review of Psychology*, *56*(Volume 56, 2005), 337–363. https://doi.org/10.1146/annurev.psych.55.090902.141449

Wells, W. M., Viola, P., Atsumi, H., Nakajima, S., & Kikinis, R. (1996). Multi-modal volume registration by maximization of mutual information. *Med Image Anal*, *1*(1), 35–51. https://doi.org/10.1016/S1361-8415(01)80004-9

White, N., Roddey, C., Shankaranarayanan, A., Han, E., Rettmann, D., Santos, J., Kuperman, J., & Dale, A. (2010). PROMO: Real-time prospective motion correction in MRI using image-based tracking. *Magn. Reson. Med*, *63*(1), 91–105. https://doi.org/10.1002/mrm.22176

Wu, X., Yu, G., Zhang, K., Feng, J., Zhang, J., Sahakian, B. J., & Robbins, T. W. (2022). Symptom-Based Profiling and Multimodal Neuroimaging of a Large Preteenage Population Identifies Distinct Obsessive-Compulsive Disorder–like Subtypes With Neurocognitive Differences. *Biological Psychiatry : Cognitive Neuroscience and Neuroimaging*, *7*(11), 1078–1089. https://doi.org/10.1016/j.bpsc.2021.06.011

XGBoost Developers. (2022). *XGBoost Parameters—Xgboost 3.1.0-dev documentation*. https://xgboost.readthedocs.io/en/latest/parameter.html#general-parameters

Xie, C., Ma, L., Jiang, N., Huang, R., Li, L., Gong, L., He, C., Xiao, C., Liu, W., Xu, S., & Zhang, Z. (2017). Imbalanced functional link between reward circuits and the cognitive control system in patients with obsessive-compulsive disorder. *Brain Imaging Behav*, *11*(4), 1099–1109. https://doi.org/10.1007/s11682-016-9585-7

Zucker, R. A., Gonzalez, R., Feldstein Ewing, S. W., Paulus, M. P., Arroyo, J., Fuligni, A., Morris, A. S., Sanchez, M., & Wills, T. (2018). Assessment of culture and environment in the Adolescent Brain and Cognitive Development Study: Rationale, description of measures, and early data. *Developmental Cognitive Neuroscience*, *32*, 107–120. https://doi.org/10.1016/j.dcn.2018.03.004