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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% (Douglass et al., 1995; Rasmussen & Eisen, 1990). The is characterized by the presence of compulsions – ritualized behavioral or mental acts, and obsessions – intrusive and unwanted thoughts and worries (Karno et al., 1988). OCD is unique among mental illnesses in that it exhibits both externalizing and internalizing symptom domains (Guzick et al., 2019). Externalizing symptoms, like compulsivity and repetitive actions, are often outwardly disruptive, while internalizing symptoms, including anxiety and obsessions, often lead to avoidance and withdrawal (Achenbach, 2009; Shephard et al., 2021). Understanding OCD within a dual framework of internalizing and externalizing symptoms enhances our grasp of its clinical complexity and can inform more effective therapeutic strategies. 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). OCD is a clinically and etiologically highly heterogeneous disorder, characterized by various overlapping symptom dimensions (Bragdon & Coles, 2017). 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 pathways struggle to suppress unwanted thoughts and actions effectively.

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 (B. j. 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, where dysfunction 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, compulsions 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 nucleus accumbens (NAcc) and other reward-processing regions, such as the OFC, during resting-state brain activity.This increased connectivity correlates with the severity of OCD symptoms (Xie et al., 2017). Lastly, (5) the dorsal cognitive circuit is involved in executive functioning and cognitive flexibility, and dysfunction in this circuit leads to rigid thinking and challenges in emotional regulation, thus exacerbating obsessions and repetitive behaviors.

Structural Brain Abnormalities

Structural brain 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 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 emphasized by the CSTC-model, 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. This is especially 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 that evaluate 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

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). SLT 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 et al., 1984). 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

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***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, our 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 Collection Procedures

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 factors influencing health and risk factors for physical and mental health problems 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 study 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, along with weighting methods and stratified sampling within specific regions to minimize selection bias, thus increasing the generalizability of the findings (Garavan et al., 2018). 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).

Data acquisition

The data utilized in this thesis is sourced from the ABCD Data Release 5.1 (available at https://nda.nih.gov/study.html?id=2313). This repository includes high-quality longitudinal data from approximately 11,880 research participants. It comprises of a diverse range of assessments, including demographic, mental health and tabulated sMRI data (Haist & Jernigan, 2023). To ensure consistency in data analysis, this study 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

Neuroimaging data is collected multimodally. Thus, ABCD developed a harmonized MRI acquisition protocol compatible with three 3 Tesla scanner platforms: the Siemens Prisma, General Electric 750, and Philips scanners, located at 21 collection sites across the US (Casey et al., 2018). Consistent with the ABCD MRI acquisition protocol T1-weighted (T1w) anatomical images were acquired using a 3D T1w inversion-prepared RF-spoiled gradient echo sequence with 1 mm isotropic resolution (Casey et al., 2018). Prospective motion correction was applied when available (currently only on Siemens and GE scanners; (Tisdall et al., 2012; White et al., 2010)). The Siemens scanner, acquisition parameters were TR = 2500 ms, TE = 2.88 ms, TI = 1060 ms, flip angle = 8°, with a 256 × 256 matrix, 176 slices, and a 256 mm FOV (acquisition time ~6:08). The Philips scanner used TR = 6.6 ms, TE = 3.1 ms, TI = 950 ms, flip angle = 9°, matrix size 256 × 256, 225 slices, and a FOV of 256 × 240 mm (acquisition time ~5:38). And, the GE scanner, parameters included TR = 2500 ms, TE = 2.0 ms, TI = 1060 ms, flip angle = 8°, with 208 slices and the same resolution and matrix size (acquisition time ~6:09).

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 in sMRI images, they may lead to inaccuracies in cortical surface reconstruction and brain segmentation (ref).

T1w quality control during 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 consistency 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 manufacturers (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. To address this issue, T2-weighted images are registered to T1-weighted 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 in a standard space. 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, following a series of methodical steps. 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 is applied to address errors or irregularities in the surface model (Fischl et al., 2001; Segonne et al., 2007). Subsequently, 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 were labeled using the Destrieux atlas-based classification (Destrieux et al., 2010). 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). It is widely used in structural MRI studies to analyze cortical volume in neurodevelopmental research ref. 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, thus 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 for DSM-5 (KSADS-5 2.0) (Kobak et al., 2013). The KSADS-5 is a comprehensive diagnostic tool compatible with the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) criteria, facilitating the categorical approach to psychiatric diagnoses (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. Moreover, assessments are normed by informant, age, sex, and ethnicity. The resulting scores are reported as z-scores within a full T-score range, 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.*

Figure 4. illustrates the process of participant inclusion criteria. Several criteria were applied for exclusion from the study. Subjects are excluded if they lack usable imaging data or if there are missing reports from either parents or children regarding internalizing and/or externalizing behaviors. Subjects are excluded from the study if they are “currently” prescribed common antidepressant or antipsychotic medications (list of meds?) because these drugs can significantly affect brain structure. Healthy control subjects are 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 were done in R version 4.3.3. Models were built with the xgboost package. We built four extreme gradient boosting models using XGBoost 3.0. 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 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 were 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 along with the optimized tuning parameters applied to the test dataset. 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

A graph of different colored lines

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Training

Optimal hyperparameters were selected for each model based on minimizing the RMSE for each target variable the reporting source (parent vs. child) and problem behavior domain (internalizing vs. externalizing). Optimal hyperparameter tuning are reported in Table 1., the results reveal distinct configurations of tuning parameters to optimize predictive performance across different symptom domains and reporter. In terms of internalizing symptoms, both models exhibited identical settings for tree depth, minimum child weight, column sampling, and learning rate (see table x for an overview of ting tang tang). However, the optimal number of boosting rounds was greater for the parent-reported model than for the child-reported model. Furthermore, the gamma and row sampling rates were greater in the child-reported model than in the parent-reported model. For externalizing symptoms, the tree depth, learning rate, column sampling rate, and row sampling rate were consistent across both the parent and child models. However, the gamma and minimum child weight values were higher in the child-reported model compared to the parent-reported model. Additionally, the number of boosting rounds was greater in the parent-reported model than in the child-reported model. These tuned hyperparameters reflect adjustments for model complexity and regularization that may correspond to differences in reporting sources and symptom domains.

A screenshot of a computer

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*Table 1. Optimal hyperparameter values for models predicting internalizing and externalizing symptoms based on sMRI data. Hyperparameters were independently tuned for each model. Notable differences were observed in the number of boosting rounds, gamma, and row sampling rate across reporting sources and symptom domains. These differences reflect adjustments in model complexity and regularization to optimize predictive performance.*

Testing

Model performance was evaluated using RMSE, MAE, and R² for each of the four models. For internalizing symptoms, the parent-reported model achieved an RMSE of 0.9450, R² of 0.0015, and MAE of 0.7677. The child-reported model had a similar RMSE (0.9447) but slightly lower R² (0.0002) and MAE (0.7057), suggesting modest improvements in average prediction error but limited variance explained. For externalizing symptoms, the parent-reported model had an RMSE of 0.8862, R² of 0.0006, and MAE of 0.7360. The child-reported model showed a slightly higher RMSE (0.9056), but a higher R² (0.0038) and lower MAE (0.6507), indicating somewhat better prediction accuracy and variance capture in this domain. Overall, while all models yielded low R² values—indicating limited explained variance—the lower MAE values, particularly for child-reported externalizing symptoms, suggest better precision in predicting individual scores despite limited model fit.

**A screenshot of a report

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***Table 2.***

Discussion

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