Title?

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Introduction

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). The disorder commonly arises in early life and 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 symptoms (Guzick et al., 2019). Externalizing features, like compulsivity and repetitive actions, are often outwardly disruptive and align with disorders such as attention-deficit/hyperactivity disorder (ADHD) and disruptive behavior disorders. In contrast, internalizing aspects, including anxiety, concerns, and obsessions, cause internal distress and align with conditions like depressive and anxiety disorders, often leading to avoidance or withdrawal (T. M. Achenbach, 2001). Understanding OCD within this dual framework enhances our grasp of its complexity and informs more effective therapeutic strategies. These frameworks are not only therapeutically beneficial but are also supported by empirical research (Kessler et al., 2011; Slade & Watson, 2006).

Informant Discrepancies

Liam (12 years) had been struggling with severe Obsessive-Compulsive Disorder (OCD) for several years. After starting therapy, he was showing signs of improvement. According to Liam, he felt he was making excellent progress. He managed to reduce his handwashing rituals from every hour to three times a day and had 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. 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 accurately understand and respond to surveys. However, 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. From this evaluation, we must make clear how parent and child assessments of mental health relate to one another.

Mental health problems can vary across different contexts (Bauducco et al., 2024; Beesdo et al., 2009). Children and adolescents may exhibit mental health concerns in certain environments, such as at home or school, while appearing unaffected in others, like during peer interactions. These contextual variations are evident across various domains, including conduct problems, attention, hyperactivity, and anxiety (Beesdo et al., 2009). Consequently, the source of information—whether from self, parents, other family members, healthcare professionals, or teachers—can lead to differing perceptions and understandings of the child's condition. This divergence in perspectives introduces complexities into clinical practice, research, and theory regarding child psychiatry and psychopathology(Y.-Y. Chen et al., 2017; Salbach-Andrae et al., 2009). These differences have been thoroughly examined and will be covered in more detail below. Furthermore, 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).

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, effectiveness of interventions for children is derived from reports by multiple informants (Weisz et al., 2005). For instance, depending on whether parent or teacher assessments are used to categorize the child's problem or if both are taken into account at the same time, the prevalence rates of conduct and oppositional defiant disorders in community samples vary from 1.6% to 10.2% (Offord et al., 1996). Furthermore, depending on the informant, it is typical to find inconsistent results from controlled studies evaluating psychological therapies (De Los Reyes & Kazdin, 2005). Understanding these discrepancies is crucial for accurately assessing intervention outcomes and advancing research in developmental psychopathology.

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.

Agreement as a test of validity for multiple informant (?) Child reports internalized symptoms more accurately, while parents tend to be more precise in identifying externalized symptoms (Silverman & Eisen, 1992).

MRI

In parallel, advances in neuroimaging, particularly structural MRI, have elucidated the brain's role in OCD, pointing to abnormalities within the cortico-striato-thalamo-cortical circuit and other key regions (de Wit et al., 2014; Hu et al., 2017; Picó-Pérez et al., 2020). Such findings suggest that neuroimaging biomarkers hold promise for enhancing diagnostic accuracy and understanding the neurobiological underpinnings of OCD. Despite these advancements, the integration of multi-informant assessments and neuroimaging data in pediatric OCD research remains limited.

Cortical thickness

Volume

Surface area

Machine Learning

The ability of neuroimaging to identify the neurological underpinnings of OCD has sparked interest in using MRI indices to distinguish between healthy people and OCD patients. In the most common machine learning paradigm, a computer program 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). Effectively, machine learning aims to uncover patterns within data without requiring explicit instructions, allowing the data to reveal its own insights with minimal assumptions (Nosari et al., 2024).

eXtreme Gradient Boosting

Gradient tree boosting is an advanced machine learning algorithm widely used for predictive modeling tasks. The objective is to determine a function (F(x)) that maps input variables (x={x\_1, ..., x\_n}) to an output variable (y). This is done by minimizing a specified loss function (L(y,F(x))) to achieve the most accurate approximation of the function mapping (Friedman, 2001). As an ensemble learning technique, it enhances prediction accuracy by aggregating multiple weak learners. XGBoost, a highly efficient and scalable implementation of gradient boosting, frames the boosting challenge as an optimization problem (Ren et al., 2019). It expands the conventional gradient boosting approach with several optimizations, including such as regularization (to prevent overfitting), parallel processing (for faster computation), and advanced tree pruning techniques (for better generalization) (T. Chen & Guestrin, 2016). XGBoost is able to model complex interactions within datasets, providing a robust framework for integrating diverse data types, such as combining neuroimaging data with behavioral and demographic variables.

The present study (?)

Despite advances in neuroimaging that emphasize the potential of structural MRI to uncover neurobiological correlates of OCD, discrepancies between parental and self-reports of OCD symptoms remain a significant challenge. Traditional diagnostic methods often overlook critical nuances in symptom severity and informant variability. In light of these challenges, this study aims to address the research question: "To what extent does structural brain data explain the variation in OCD symptoms as reported by youths versus their parents?" Using the ABCD dataset, the study will explore whether the machine learning model XGBoost can detect established patterns of informant discrepancies, commonly observed in psychiatric assessments.

Research question

To what extent does structural brain data explain the variation in OCD symptoms as reported by youths versus their parents?

Model building focus on a phenomena that is already well established to see whether machine learning can detect the same features of informer discrepancy on ABCD dataset

Use MRI to predict youth score vs. parent score on two dimensions.

Have difference in score as an independent variable.

Hypothesis

There will be a significant difference in the prediction accuracy of structural brain data between self-reported and parent-reported anxiety symptoms in adolescents with OCD, with an expectation of higher accuracy for self-reported symptoms.

Methods

Data Source and Collection Procedures

The Adolescent Brain and Cognitive Development (ABCD) Study comprehensive decade-long research initiative in the United States, tracking children from ages 9-10 through late adolescence and into early adulthood. It conducts annual lab-based evaluations and biannual imaging scans to assess various mental and physical health metrics (Saragosa-Harris et al., 2022; Barch et al., 2018). The ABCD Study is designed to enhance our understanding of the behavioral, genetic, neurobiological, and environmental factors influencing health and risk factors for physical and mental health problem. The study includes 12,000 children at baseline, recruited from 21 research sites across the United States (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.

Data acquisition

Questionaries

Kiddie Affective

Demographic variables

Achenbach System and Empirically Based Assessment (ASEBA)

Child Behavior Checklist (CBCL).

The CBCL is a component of the ASEBA and is used to assess behavioral, emotional, or social problems in children (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”. It 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, including (1) Anxious/Depressed, (2) Withdrawn/Depressed, (3) Somatic Complaints, (4) Social Problems, (5) Thought Problems, (6) Attention Problems, (7) Rule Breaking Behavior, (8) Aggressive Behavior. Meanwhile, the more recently developed seven DSM-Oriented Scales align with diagnostic categories outlined in the Diagnostic and Statistical Manual of Mental Disorders. They include; (1) OCD Problems, (2) Depressive Problems, (3) Anxiety Problems, (4) Somatic Problems, (5) Attention Deficit/Hyperactivity Problems, (6) Oppositional Defiant Problems, (7) Conduct Problems (American Psychiatric Association, 2013; Nelson et al., 2001). Furthermore, these scales are grouped into three high-level domains known as (1) Internalizing Problems (which combines Anxious/Depressed, Withdrawn/Depressed, and Somatic Complaints), (2) Externalizing Problems (which combines Rule-Breaking Behavior and Aggressive Behavior), and a (3) Total Problems score that sums all problem items. 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.

Brief Problem Monitor (BPM).

The BPM 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." 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).

Structural MRI

High-resolution T1-weighted and T2-weighted 3D structural images were acquired using Siemens, Philips, and GE 3T MRI scanners. Preprocessing includes correcting for bias field, distortion, and resampling (Hagler et al., 2019). Images were corrected for gradient nonlinearity distortions (Jovicich et al., 2006), and T2w images were registered to T1w images using a mutual information-based approach (Wells et al., 1996). Intensity non-uniformity was corrected through tissue segmentation and sparse spatial smoothing. All images were resampled to 1 mm isotropic resolution and rigidly aligned to a standard atlas space. Regions of interest (ROIs) were defined 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. It provides 74 bilateral regions (148 total). While it excludes subcortical structures, it is widely used in structural MRI studies to analyze cortical volume, thickness, and sulcal depth in neurodevelopmental and neurodegenerative research.

Sample

Statistical analyses/Preliminary analyses(?)

Modelling approach(?)

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