Title? Discrepancies Between Parental and Child Reports in Predicting OCD Symptomatology and Diagnosis: A Multimodal Approach Using Structural MRI and XGBoost Modeling on the ABCD Dataset

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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).

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. The family had rearranged the house to facilitate his progress—stocking rooms with hand sanitizers and scheduling regular therapist meetings to help him during challenging times. 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 supply 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.

Additionally, 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.

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. 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.(GPT)

This divergence in perspectives introduces complexities into clinical practice, research, and theory regarding child psychiatry and psychopathology(Chen et al., 2017; Salbach-Andrae et al., 2009). These differences have been thoroughly examined and will be covered in more detail below (Van Roy et al., 2010). 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).

Informant Discrepancies

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 example, the prevalence rates of conduct and oppositional defiant disorders in community samples range from 1.6% to 10.2%, depending on whether parent or teacher ratings are relied on to classify disorder in the child or whether both are considered simultaneously (Offord et al., 1996). Prevalence of classification of disorder ranges widely in clinic samples as well. When relying on parent or teacher ratings, or combining information from both, prevalence of conduct disorder ranges from 9.7% to 23%, and emotional disorder (anxiety, depression) ranges from 10.3% to 36.2% (MacLeod et al., 1999) (De Los Reyes & Kazdin, 2005). 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. Child reports internalized symptoms more accurately, while parents tend to be more precise in identifying externalized (Silverman & Eisen, 1992).

Research conducted since 1987 has primarily focused on understanding the characteristics associated with informant discrepancies, potential biases in informants' reports, and the impact these discrepancies have on the conclusions drawn from research studies. (Reyes, 2013)

Agreement as a test of validity for multiple informant

Research indicates discrepancies and varying accuracy in symptom reporting, with no clear consensus. Child reports internalized symptoms more accurately, while parents tend to be more precise in identifying externalized (Silverman & Eisen, 1992). It can be challenging for clinicians to make a diagnosis if data from different sources are conflicting. Disagreement between children and their parents about target problems can be problematic when it comes to setting treatment goals, which can, ultimately, lead to poorer treatment outcomes [35]. Studying moderators of parent–youth agreement may facilitate diagnostic processes [36]. Research suggests that agreement between parents and children is related to factors such as a child’s age [31,35], gender [37,38] and type and severity of disorder – especially anxiety and depression [39] – and parental psychopathology [39–42]. Studying those moderators may guide clinicians in assessing which reports have greater veracity [35,42,43]. (Jónsdóttir et al., 2022)

MRI

Magnetic resonance imaging (MRI) research has shown that OCD patients exhibit structural and functional abnormalities in a number of brain areas, primarily in the cortico-striato-thalamo-cortical (CSTC) circuit (de Wit et al., 2014; Hu et al., 2017; Picó-Pérez et al., 2020). The ability of neuroimaging to identify the neurological underpinnings of OCD has sparked interest in utilizing MRI indices to distinguish between healthy people and OCD patients. Machine learning techniques have been presented in order to execute the diagnostic categorization and find the neuroimaging biomarkers. Detecting subtle and geographically dispersed effects of neuroimaging data [13] and allowing inference at the individual level instead of the group level [14] are two advantages of machine learning techniques. For instance, one of the most popular machine learning models is the support vector machine (SVM). one of the most popular machine learning models, has been used to develop models for diagnosing mental illnesses such autism [19, 20], depression [17, 18], and schizophrenia [15, 16]. In order to distinguish between OCD patients and healthy people, we employed MRI data and machine learning techniques in this work, such as support vector machines (SVM) and two additional popular classifiers: logistic regression (LR) and random forest (RF). (Huang et al., 2023)

Cortical thickness

Sulcal depth

Surface area

eXtreme Gradient Boosting

 XGBoost, renowned for its capability to model complex interactions within datasets, provides a robust framework for synthesizing high-dimensional neuroimaging data with behavioral and demographic variables. (GPT)

Boosting: Boosting is another way to create a strong learner with an ensemble of weak ones. Compared with bagging, base learners of boosting are generated differently. Here base learners are trained sequentially so that later learners can be trained based on the results of the former learners with more focus on minimizing the errors. We first train the initial base learner B1 with the data set D1 generated by sampling with replacement and calculate the errors Errors(yj, B1(xj)) for (yj, xj) ∈ D1. Then, for {(yj, xj)} with large errors, they will be assigned a high weight to be sampled into the new data set D2 which is used to generate the next base learner B2. After generating a sequence of base learners, we combine these learners to get a final learner. A famous example is AdaBoost [2], which usually has good performance in classification problems. Other examples include Gradient Boosting [8] which views the boosting problem as an optimization problem and XGboost [9] (eXtreme Gradient Boosting) which is an efficient and scalable implementation of Gradient Boosting. (Ren et al., 2019)

The present study

This thesis aims to address these gaps by utilizing the Adolescent Brain Cognitive Development (ABCD) dataset to investigate the intersections of parental versus child reports, structural MRI markers, and critical demographic variables in understanding OCD symptomatology. Employing the advanced machine learning model XGBoost, this study seeks to develop a robust predictive framework for OCD diagnosis that acknowledges informant discrepancies and incorporates neuroimaging insights. By combining sMRI data with behavioral reports, this research endeavors to present a more comprehensive picture of pediatric OCD, thus informing more nuanced clinical assessments and interventions.

This thesis seeks to address these gaps by leveraging the Adolescent Brain Cognitive Development (ABCD) dataset to explore the intersection of parental versus child reports, structural MRI markers, and key demographic variables in understanding OCD symptomatology. Employing a state-of-the-art machine learning model, XGBoost, this study aims to develop a robust predictive framework for OCD diagnosis that acknowledges informant discrepancies and incorporates neuroimaging insights. By doing so, this research endeavors to offer a more comprehensive picture of pediatric OCD, thereby informing more nuanced clinical assessments and interventions. (GPT) Advancements in neuroimaging have illuminated the potential of structural MRI (sMRI) to reveal underlying neurobiological correlates of OCD. Alterations in the cortico-striato-thalamo-cortical circuit and other associated brain regions point toward objective biomarkers that could complement traditional assessment methods. By combining sMRI data with behavioral reports, researchers can deepen their understanding of OCD's etiology and progression. (GPT)

Research question

To what extent does structural brain data explain the variation in anxiety 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 four 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 GAD, with an expectation of higher accuracy for self-reported symptoms.

The purpose of this study was to examine agreement between youths and their parents regarding psychiatric problems, at a symptom level, using the CBCL. There are certain limitations of measuring parent–child agreement using the diagnostic approach, such as the loss of information (e.g. severity or magnitude of disagreement) when data are dichotomized. Another approach is to measure symptom agreement, which would make a quantitative distinction between parent’s and child’s ratings [26]. Thus, we will also examine agreement at a symptom level using the Achenbach System of Empirically Based Assessment (ASEBA) in an Icelandic outpatient clinical sample, as well as studying the influence of age, gender, attention-deficit/ hyperactivity, anxiety disorder and depressive disorder on parent–youth agreement. (Jónsdóttir et al., 2022)

Methods

Data Source and Collection Procedures

The Adolescent Brain and Cognitive Development (ABCD) Study is a decade-long investigation in the US, tracking children from ages 9-10 through late adolescence and early adulthood. This study 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 issues. It 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

**Demographics**

ASEBA – Achenbach System and Empirically Based Assessment

**The Child Behavior Checklist (CBCL)** is a component of the Achenbach System of Empirically Based Assessment (ASEBA) and is used to assess behavioral, emotional, or social 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 items 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 including (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.

**The Brief Problem Monitor** 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).

MRI

High-resolution T1-weighted (T1w) and T2-weighted (T2w) 3D structural images were acquired using Siemens, Philips, and GE 3T MRI scanners. Preprocessing includes steps for bias field, distortion, and/or motion correction (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). It uses a sulco-gyral classification, distinguishing between exposed gyri and buried sulci based on mean curvature and convexity. The atlas provides 74 bilateral regions (148 total). Labels were manually defined on 12 brains following Duvernoy’s nomenclature and automated using a probabilistic approach incorporating cortical geometry and relative brain locations, achieving ~80-85% accuracy (Destrieux et al., 2010). 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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