Registered Report

Biological Psychiatry: GOS

Differences in Head Motion During Functional Magnetic Resonance Imaging Across Pediatric Neuropsychiatric Disorders

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ABSTRACT

BACKGROUND: Robust correction for head motion during functional magnetic resonance imaging is critical to avoid artifact-driven findings. Despite head motion differences across neuropsychiatric disorders, pediatric head motion across a range of diagnoses and covariates has not yet been evaluated. We tested 4 preregistered hypotheses: 1) externalizing disorder diagnoses will associate with more head motion during scanning; 2) internalizing disorder diagnoses will associate with less motion; 3) among children without attention-deficit/hyperactivity disorder, externalizing disorders will associate with more motion; and 4) among children with attention-deficit/hyperactivity disorder, comorbid internalizing disorders will associate with less motion.

METHODS: Healthy Brain Network data releases 1.0–7.0 (n = 971) were analyzed in a discovery phase, and additional data released by February 29, 2024 (n = 437) were used in confirmatory analyses. Linear mixed-effects models were fitted with in-scanner head motion as the dependent variable. Binary independent variables of interest assessed for the presence or absence of externalizing or internalizing disorders.

RESULTS: The confirmatory sample did not show significant associations between head motion and externalizing or internalizing disorders or support for the preregistered hypotheses. Across samples, there was a consistent interaction between age and neurodevelopmental diagnoses such that age-related decreases in head motion were attenuated in children with neurodevelopmental disorders.

CONCLUSIONS: Head motion remains an important confound in pediatric neuroimaging that may be associated with many factors, including neuropsychiatric symptoms, age, cognitive and physical attributes, and interactions among these variables. This work takes a step toward parsing these complex associations, focusing on neuropsychiatric diagnoses, age, and their interaction.

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The critical need to avoid artifacts in neuroimaging results by detecting, mitigating, and correcting for head motion during functional magnetic resonance imaging (fMRI) has gained prominence over the past decade. Although some head motion is inevitable, even small head motions can lead to spurious functional activations if not addressed (1–3). Managing head motion artifacts is especially important in pediatric and developmental studies because inverse associations between age and head motion across childhood and adolescence are well established (3–6).

fMRI is a central tool for understanding brain mechanisms that underlie neuropsychiatric disorders, but studies have reported differences in head motion during fMRI across various neuropsychiatric conditions, potentially confounding results and interpretation. For example, increased head motion during scanning has been observed in participants with attention-deficit/hyperactivity disorder (ADHD) (5,7), autism spectrum disorder (ASD) (5,8), and elevated externalizing symptoms (4,9). Conversely, while head motion during MRI in internalizing disorders has not been systematically studied to date, shared symptoms across internalizing disorders such as psychomotor retardation, perfectionism, and increased attentiveness to research personnel's instructions to remain still could contribute to decreased head motion during fMRI (10). For example, consistent with common symptoms of perfectionism and a drive to feel "just right" in obsessive-compulsive disorder (11), previous work from our laboratory has suggested a trend toward reduced motion in children with obsessive-compulsive disorder (12,13). If not managed appropriately, differences in head motion across disorders can fundamentally confound studies seeking to uncover altered brain function (14).

Numerous methods are used to mitigate head motion artifacts at various stages of a study. These include prescan training with mock scanners and motion simulators [e.g., MoTrak (15,16)] (17–20), head molds to reduce movements (21), online monitoring of head motion [e.g., FIRRM (22), real-time feedback (23)], acquisition with prospective motion correction (24,25), and postscan processing. Regardless, even with recent advances in acquisition and preprocessing pipelines (26), motion-related artifacts cannot be completely

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removed from fMRI data (27). Thus, current best-practice techniques for removing motion artifacts during data processing require excluding data points or entire participants who have extremely protracted or large movements (27,28). Additionally, head motion is linked to many other variables that may complicate neuropsychiatric studies. For example, higher performance on cognitive measures, such as IQ tests (9,29), and higher socioeconomic status (SES) (4) have been associated with reduced head motion, while higher body mass index (BMI) may be linked to greater head motion (4,30–32). Despite these findings, systematic evaluations of pediatric head motion across psychiatric diagnoses accounting for age and other covariates are lacking.

The Healthy Brain Network (HBN) Biobank offers a large-scale dataset ideal for evaluating head motion across diagnostic categories in youths (33). The HBN Biobank contains MRI, psychiatric, cognitive, and demographic data from 5- to 21-year-old participants with a range of psychiatric diagnoses. Confirming previous work, correlational analyses in the initial data release (n = 664) showed a negative association between head motion and age and a positive association between motion and externalizing symptoms (33). Using a larger sample and stricter methodology, the current work examines fine-grained associations between head motion and multiple psychiatric diagnoses. We also aimed to parse potential effects of comorbidity and account for important variables from the literature, such as age, BMI, and IQ, as well as screen other sociodemographic factors that may be relevant to this sample.

HBN study data releases 1.0–7.0 (published April 13, 2020) were explored during an initial discovery phase. Based on discovery analyses and previous literature, specific hypotheses were registered (https://doi.org/10.17605/OSF.IO/X93CE). All new data released by February 29, 2024, were used for confirmatory analyses. We highlight 4 hypotheses of interest. All analyses covaried for comorbid diagnoses, age, sex, IQ, BMI, and SES. Hypothesis 1) Children diagnosed with an externalizing disorder (ADHD, disruptive disorders) will exhibit more head motion than children without externalizing diagnoses. Hypothesis 2) Children diagnosed with an internalizing disorder (anxiety, depressive, obsessive, trauma and stressor-related disorders) will exhibit less head motion than children without internalizing disorders. Given high rates of ADHD in the discovery subsample, we tested hypotheses 1 and 2 among children without and with diagnoses of ADHD. Hypothesis 3) We hypothesized that among children with no ADHD diagnosis, having an externalizing disorder diagnosis would be related to higher head motion. Hypothesis 4) We hypothesized that among children with an ADHD diagnosis, a comorbid internalizing disorder would be related to less head motion.

Collectively, these hypotheses address important questions about how head motion during fMRI differs across children with neuropsychiatric diagnoses. These hypotheses also begin to unpack how interrelated factors, such as IQ, may affect the associations between diagnoses and in-scanner head motion. A better understanding of these associations may help identify potential limitations and confounding factors in imaging studies that involve participants with neuropsychiatric disorders and may guide researchers in estimating likely motion-related data exclusions to ensure adequate sample sizes during the design of future studies. Furthermore, findings pave the way for future work to examine the relative effects of motion-reducing strategies such as mock scanning in different pediatric populations. For example, future research may benefit from scheduling additional time or study visits dedicated to multiple mock scanning sessions for children with externalizing disorders, while studies of participants with anxiety or depressive disorders may be able to schedule shorter/fewer mock scan sessions without compromising scan quality.

METHODS AND MATERIALS

Participants

The HBN Biobank is an ongoing initiative that aims to collect a broad range of behavioral, imaging, and other data from a community sample of 10,000 children and adolescents (ages 5–21 years) from the New York City area (33). Participants completed anatomical MRI scans and up to 2 runs of resting-state fMRI, 2 runs of movie-watching fMRI, and 3 runs of fMRI while performing a peer task (33,34) at one of the 3 scanners.

This study examined HBN data releases 1.0–7.0 (published Apr 13, 2020) in a discovery phase (see the Supplement) and addressed specific hypotheses listed herein using the data that had been publicly released by Feb 29, 2024, in confirmatory analyses. Critically, the motion quality assurance (QA) data required for confirmatory analyses had not been released as of submission of stage 1 of this registered report.

In addition to the HBN exclusion criteria (33), participants were excluded from the current analyses if they did not have at least 1 fMRI run with head motion metrics, did not complete the full psychiatric diagnostic evaluation, or were given a diagnosis of intellectual disability, bipolar disorder, neurocognitive disorders, schizophrenia, or substance use disorder. These disorders were rare in the discovery dataset, thus limiting statistical power to assess their association with head motion, but they could confound associations with other variables of interest. For each analysis, participants were excluded if they were missing data for 1 or more of the analyzed variables.

Head Motion Data

For each fMRI sequence, automated QA metrics, including head motion parameters, were generated by HBN using the Preprocessed Connectomes Project QA Protocol (https://fcon_1000.projects.nitrc.org/indi/cmi_healthy_brain_network/MRI_EEG.html#Data%20Quality) (35,36). Herein, the dependent variable of interest was in-scanner head motion, which was quantified as the percentage of frames/time points per run flagged as outliers based on a Jenkinson framewise displacement cutoff of 0.2 mm (37), as provided by HBN's QA protocol. The Jenkinson framewise displacement threshold of 0.2 mm is consistent with best practices that have been proposed in the literature (38). The percentage of outlier frames is representative of the amount of usable data that are retained for analysis after movement correction (e.g., scrubbing or censoring) as opposed to more general metrics like mean framewise displacement (33,39).

Functional runs from movie watching, peer task, and resting state were included in all analyses. The type of run was coded into a 3-level categorical variable used as a covariate (see the Supplement).

Clinician-Administered Assessments

As previously described (33), each participant was assessed by a licensed clinician using a computerized, web-based Schedule for Affective Disorders and Schizophrenia-Children's version (40). Each participant was assigned up to 10 DSM-5 diagnoses by HBN clinical team consensus based on the Schedule for Affective Disorders and Schizophrenia-Children's version interview, parent-reported symptoms (described below), and other information collected during study participation. For the current analyses, given the high rates of multiple comorbid diagnoses and high prevalence of ADHD in this sample, individual diagnoses were categorized as externalizing (ADHD and disruptive), internalizing (anxiety, depressive, obsessive, and trauma- and stressor-related), and neurodevelopmental (ASD, specific learning, language, and motor) disorders. The categories are nonexclusive; for example, a participant diagnosed with ADHD and generalized anxiety disorder would be coded as present for both the externalizing and internalizing disorder variables and absent for the neurodevelopmental disorder variable.

To assess IQ, participants completed an age-appropriate intelligence test, the Wechsler Intelligence Scale for Children for ages 6 to 17 (41) or the Wechsler Adult Intelligence Scale for ages ≥18 (42). Full Scale IQ scores were examined.

Parent-Reported Symptom Data

Parents of participants ages 6 to 18 were administered the Child Behavior Checklist (CBCL) (43). We used the following 8 narrowband symptom scales as dimensional clinical measurements (43), calculated as T-scored sums of subsets of the CBCL items by HBN: Aggressive Behavior, Anxious/Depressed, Attention Problems, Rule-Breaking Behavior, Somatic Complaints, Social Problems, Thought Problems, and Withdrawn/Depressed.

Demographic and Physical Data

Participants' age and sex (dummy coded) were used as reported by HBN.

SES was reported by parents/guardians. In this work, 2 variables quantified SES in each analysis: the Barratt Simplified Measure of Social Status total score (44) and the highest/maximum level of parental education obtained (see the Supplement).

BMI was reported by the HBN study. Because BMI naturally increases across the study age range (5–21 years), we used age- and sex-adjusted BMI scales from the U.S. Centers for Disease Control and Prevention to calculate BMI *z* scores (https://www.cdc.gov/growthcharts/extended-bmi-data-files.htm). BMI *z* scores <-5 ($n = 2$) or >5 ($n = 4$) were excluded from analyses as statistical outliers.

Analyses

Associations between diagnoses and head motion were modeled using linear mixed-effects (LME) models [R packages lme4 (45) and lmerTest (46)], summarized in Table S1. In-scanner head motion (percentage of frames excluded) was examined as the dependent variable. LME models included a random effect for participant to account for repeated measures together with a fixed effect for series type (rest, task, or movie). All models included fixed effects for age, sex, IQ, *z*-scored BMI, Barratt Simplified Measure of Social Status total score, and highest parental education. Prior to modeling, numerical variables (age, IQ, Barratt Simplified Measure of Social Status, parental education) were *z* scored.

As a positive control, we first confirmed expected inverse associations between age and head motion. We anticipated replicating previous findings wherein participant age has a robust association with head motion across the pediatric age range, with older participants displaying lower head motion than younger children (3–6).

Hypotheses 1 and 2 were tested using a single LME model, with 3 binary fixed effects for whether the participant had diagnosed internalizing, externalizing, or neurodevelopmental disorders as predictors of interest. A significant positive coefficient for externalizing disorders (diagnosis present $>$ absent) would indicate support for hypothesis 1. A significant negative coefficient for internalizing disorders (diagnosis present $<$ absent) would indicate support for hypothesis 2.

For hypothesis 3, an LME model was used to examine the subset of participants without a clinician-consensus diagnosis of ADHD. The predictors of interest included 3 binary fixed effects for whether the participant had any diagnosed internalizing, externalizing, or neurodevelopmental disorders. A significant positive coefficient for the binary variable encoding externalizing disorder diagnoses would indicate support for hypothesis 3.

For hypothesis 4, an LME model was used to examine the subset of participants with a clinician-consensus diagnosis of ADHD (any subtype). The predictors of interest included 2 binary fixed effects for whether the participant had any diagnosed internalizing or neurodevelopmental disorders. A significant negative coefficient for the dummy variable encoding internalizing disorder diagnoses would indicate support for hypothesis 4.

We also performed several exploratory analyses to examine more fine-grained diagnostic categories, dimensional symptom scales, and age-related interactions. In exploratory analysis 1, we fitted an LME model with the top 2 most prevalent disorder categories for each group to examine specific diagnoses more closely. Specifically, predictors of interest were binary fixed effects for the presence or absence of the following categories of disorders: anxiety, depressive, other internalizing, ADHD, disruptive, autism spectrum, and other neurodevelopmental.

In exploratory analysis 2, we fitted an LME model with the narrowband dimensional symptom scales from the CBCL instead of diagnostic categories. Our predictors of interest were all 8 narrowband CBCL symptom scales. Because CBCL symptom scales are often highly correlated, we calculated the generalized variance inflation factor [R package car (47)] to check for collinearity of predictors; we considered this model invalid due to multicollinearity concerns if the generalized variance inflation factor was >10 for any predictors of interest (48,49).

For exploratory analysis 3, we fitted an LME model similar to that described above for testing hypotheses 1 and 2 but with additional interaction terms between age (scaled) and each of the internalizing, externalizing, and neurodevelopmental diagnosis categories. The predictors of interest were these interaction terms.

RESULTS

After approval of the stage 1 registered report, MRI QA and additional phenotypic data were made available for HBN data

releases 8 to 10. We performed the analyses listed under Analyses in a confirmatory sample comprising all eligible participants for whom complete data, as defined in Methods and Materials, were available as of February 29, 2024, who were not included in the discovery sample.

Participants

The confirmatory sample contained 3056 eligible fMRI runs across 437 participants (Figure 1). Summary statistics are shown in Table 1. Figure S3 shows the distribution of the head motion across participants.

Positive Control: Inverse Relationship Between Age and Head Motion

We confirmed the expected association between older age and less head motion across all models, for example $t_{430} = -5.56$ ($p < 10^{-7}$) in the total sample (Table 2).

Specific Hypotheses 1 and 2: Main Effects of Externalizing and Internalizing Disorders

The first LME (n = 437), which assessed hypotheses 1 and 2 (Table 2), revealed no significant associations between head motion and externalizing disorders (beta = 0.0010, $t_{426} = 0.27$, p = .79) or internalizing disorders (beta = −0.0038, $t_{425} = -1.11$, p = .27), thus failing to support either hypothesis. By comparison, in the discovery sample (n = 971) (Table S2), externalizing disorders were significantly associated with greater motion, and internalizing disorders were significantly associated with reduced motion.

The confirmatory model showed a significant positive association between head motion and neurodevelopmental disorders (beta = 0.0072, $t_{426} = 2.12$, p = .035), which was not present in the discovery sample.

In both samples, higher participant IQ, female sex, and higher BMI were associated with reduced head motion. There were no significant effects of run type or SES in the confirmatory sample, although these covariates were significant in the discovery sample.

Hypothesis 3: Effect of Externalizing Disorders in Participants Without ADHD

The LME performed on the subset of confirmatory sample participants with no diagnosed ADHD (n = 141) revealed no evidence to support hypothesis 3 (Table S8). Having a diagnosis of 1 or more internalizing disorders was associated with a significant decrease in head motion (beta = −0.014, $t_{131} = -2.16$, p = .032), but there was no effect of an

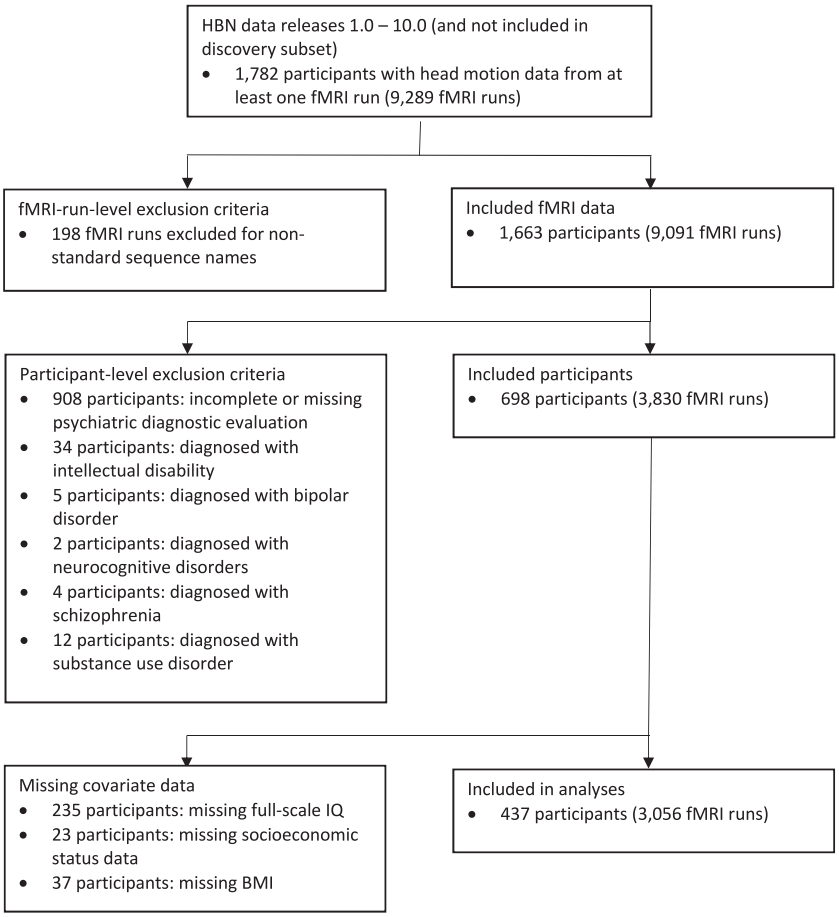

Figure 1. Flowchart of participant-level and functional magnetic resonance imaging (fMRI) run–level exclusions in the confirmatory data subset. BMI, body mass index; HBN, Healthy Brain Network.

Table 1. Summary Statistics for Each Dependent Variable of Interest Across Included Participants in Each Sample

	Discovery Sample	Confirmatory Sample	t or χ^2 Statistic (p Value)
Numerical Variables, Mean (SD)			
Age, Years	10.2 (3.0)	9.9 (2.6)	1.94 (.052)
Number of Diagnoses	2.1 (1.5)	2.7 (1.7)	−5.68 ($<2^{-8}$[a])
Body Mass Index, Raw	20.8 (5.6)	18.9 (4.3)	6.81 ($<2^{-8}$[a])
Body Mass Index, z Score	0.80 (1.3)	0.45 (1.1)	5.21 ($<2^{-8}$[a])
IQ	99.6 (16.0)	102.3 (16.1)	−2.90 (.004[a])
BSMSS Total Score	49.5 (13.6)	50.0 (14.6)	−0.67 (.50)
Highest Parental Education[b]	18.8 (2.8)	18.9 (3.2)	−0.59 (.56)
Percentage of Frames Flagged as Outliers During fMRI	7.6% (3.7%)	7.6% (3.6%)	−0.17 (.87)
Mean FD During fMRI	0.42 (0.63)	0.39 (0.43)	1.20 (.23)
Categorical Variables, n (%)			
Sex, Female	332 (34.2%)	137 (31.4%)	0.97 (.32)
Diagnosis Categories			
Externalizing disorder	654 (67.4%)	309 (70.7%)	1.42 (.23)
Internalizing disorder	347 (35.7%)	199 (45.5%)	11.79 (.0006[a])
Neurodevelopmental disorder	449 (46.2%)	225 (51.5%)	3.12 (.077)
Specific Diagnosis of ADHD	624 (64.3%)	296 (67.7%)	1.45 (.23)
No Diagnoses	83 (8.5%)	31 (7.1%)	0.67 (.41)

ADHD, attention-deficit/hyperactivity disorder; BSMSS, Barratt Simplified Measure of Social Status; FD, framewise displacement; fMRI, functional magnetic resonance imaging.
[a]Indicates a statistically significant difference between samples.
[b]Highest parental education measured as described in Supplement, page 3.

externalizing disorder diagnosis (beta = −0.016, t_{130} = −1.52, p = .13). In the comparable subset of the discovery sample (n = 347) (Table S3), externalizing disorders were associated with a trend-level increase in head motion.

Hypothesis 4: Effect of Internalizing Disorders in Participants With ADHD

The subset of confirmatory sample participants who were given a diagnosis of ADHD (n = 296) (Table S9) did not support hypothesis 4. This model revealed a significant association between neurodevelopmental disorders and increased head motion (beta = 0.0087, t_{287} = 2.18, p = .030) but no significant effect of internalizing disorders (beta = 0.0011, t_{286} = 0.28, p = .78). The comparable subset of the discovery sample (n = 624) (Table S4) showed a trend-level association between reduced head motion and internalizing disorders but no association with neurodevelopmental disorders.

Exploratory Analysis 1: Finer Diagnostic Categories

In the confirmatory sample (n = 437) (Table 3), having an ASD diagnosis was associated with a significant increase in head motion (beta = 0.015, t_{416} = 2.72, p = .0068). No other diagnoses, including ADHD, were associated with significant differences in head motion.

Table 2. Fixed Effects From the Linear Mixed-Effects Model Examining Association Between Head Motion During Functional Magnetic Resonance Imaging, Neuropsychiatric Diagnosis Categories, Series Type, and Demographic and Cognitive Covariates in the Confirmatory Sample

	Standardized Estimate	Standard Error	t Statistic	p Value
(Intercept)	0.075	0.0042	t_{487} = 17.9	$<10^{-15}$[a]
Neuropsychiatric Diagnosis Categories				
Internalizing	−0.0038	0.0034	t_{425} = −1.11	.27
Externalizing	0.0010	0.0037	t_{426} = 0.27	.79
Neurodevelopmental	0.0072	0.0034	t_{426} = 2.12	.035[a]
Series Type, Compared With Rest				
Movie	−0.0007	0.0017	t_{2155} = −0.38	.70
Peer	−0.0006	0.0017	t_{2151} = −0.32	.75
Age	−0.011	0.0021	t_{430} = −5.56	$<10^{-7}$[a]
Sex, Female	−0.0079	0.0036	t_{427} = −2.19	.029[a]
IQ	−0.0046	0.0018	t_{429} = −2.49	.013[a]
Barratt Total Score	−0.0013	0.0023	t_{425} = −0.58	.56
Highest Parental Education	0.0005	0.0022	t_{426} = 0.21	.83
Body Mass Index	−0.0054	0.0017	t_{421} = −3.23	.0014[a]

[a]Indicates p value significant at .05 threshold.

Table 3. Fixed Effects From the Linear Mixed-Effects Model Examining Associations Between Head Motion During Functional Magnetic Resonance Imaging, Neuropsychiatric Diagnosis Categories, Series Type, and Demographic and Cognitive Covariates

	Standardized Estimate	Standard Error	*t* Statistic	*p* Value
(Intercept)	0.074	0.0041	$t_{486} = 18.3$	$<10^{-15}$[a]
Neuropsychiatric Diagnosis Categories				
Anxiety	−0.0017	0.0035	$t_{422} = -0.50$	.62
Depressive	0.0017	0.0061	$t_{414} = 0.29$	.77
Other Internalizing	−0.0049	0.0056	$t_{413} = -0.86$	.39
ADHD	0.0025	0.0037	$t_{422} = 0.68$	.50
Disruptive	0.0003	0.0046	$t_{424} = 0.07$	.94
Autism spectrum	0.015	0.0055	$t_{416} = 2.72$	.0068[a]
Other neurodevelopmental	0.0022	0.0035	$t_{423} = 0.64$	.52
Series Type, Compared With Rest				
Movie	−0.0007	0.0017	$t_{2155} = -0.38$	.71
Peer	−0.0006	0.0017	$t_{2151} = -0.32$	.75
Age	−0.012	0.0021	$t_{426} = -5.78$	$<10^{-7}$[a]
Sex, Female	−0.0066	0.0036	$t_{424} = -1.81$	.070
IQ	−0.0049	0.0019	$t_{426} = -2.56$	.011[a]
Barratt Total Score	−0.0009	0.0023	$t_{421} = -0.39$	.70
Highest Parental Education	0.0005	0.0023	$t_{422} = 0.22$	.83
Body Mass Index	−0.0053	0.0017	$t_{417} = -3.14$	.0018[a]

ADHD, attention-deficit/hyperactivity disorder.
[a]Indicates *p* value significant at .05 threshold.

Exploratory Analysis 2: Dimensional Symptom Scales

In the confirmatory sample ($n = 437$) (Table 4), higher scores on the CBCL Attention Problems subscale showed a trend-level association with more head motion (beta = 0.00040, $t_{421} = 1.74$, $p = .083$), consistent with the discovery sample. Generalized variance inflation factor values were <5 for all variables, indicating minimal biasing of results due to collinearity between predictors.

Exploratory Analysis 3: Interactions Between Diagnostic Categories and Age

A significant interaction between diagnosis and age was detected in the confirmatory sample ($n = 437$) (Table 5) such that age-related decreases in head motion were lessened in participants with neurodevelopmental disorders (beta = 0.010, $t_{428} = 2.48$, $p = .014$), consistent with the discovery sample (Table S7). The confirmatory model also revealed an association between neurodevelopmental disorder diagnoses and more head motion (beta = 0.0079, $t_{422} = 2.31$, $p = .021$), which was not present in the discovery sample. No main effects of internalizing or externalizing disorder diagnoses or interactions of these with age were detected in the confirmatory sample. Higher participant IQ and BMI were associated with reduced head motion in both samples.

DISCUSSION

Head motion during fMRI is an important source of artifact, especially in pediatric samples. In this study, we examined head motion during scanning across neuropsychiatric disorders. Despite hypotheses that were supported in the discovery sample and the literature, we did not find evidence for our 4 primary hypotheses in the confirmatory sample. These hypotheses were externalizing disorders would associate with more and internalizing disorders would associate with less head motion during fMRI; among children without ADHD, externalizing disorders would associate with higher head motion; and among children with ADHD, comorbid internalizing disorders would associate with less head motion. However, we found that age-related decreases in head motion were attenuated in children with neurodevelopmental disorders.

Externalizing and Internalizing Disorders

We hypothesized but did not find increased head motion during fMRI in participants with externalizing disorders in the confirmatory sample. Among the subset of confirmatory sample participants without an ADHD diagnosis, having at least 1 internalizing disorder was associated with reduced head motion in the scanner. However, this finding did not generalize to the broader confirmatory sample that includes participants with ADHD. There was a trend-level association in the confirmatory sample between CBCL Attention Problems scores and head motion, which was consistent with a significant association in the discovery sample.

These results suggest that a dimensional symptom-based approach to understanding head motion may usefully supplement a categorical diagnosis-based approach. Because the dimensional scales were parent reported, and categorical diagnoses were determined by clinician consensus, this finding may also reveal differences across respondents such that clinical thresholds for attention deficits or hyperactivity may not fully correspond to caregivers' perception of problems within this domain.

Neurodevelopmental Disorders

Our specific hypotheses focused on head motion in internalizing and externalizing disorders, but all models also

Table 4. Fixed Effects From the Linear Mixed-Effects Model Examining Associations Between Head Motion During Functional Magnetic Resonance Imaging, Dimensional Symptom Scales From the CBCL, Series Type, and Demographic and Cognitive Covariates

	Standardized Estimate	Standard Error	*t* Statistic	*p* Value
(Intercept)	0.077	0.017	$t_{423} = 4.46$	$<10^{-4}$[a]
CBCL Dimensional Symptom Scales				
Aggressive behavior	0.00031	0.00032	$t_{424} = 0.96$	.34
Anxious/depressed	−0.00020	0.00029	$t_{423} = -0.70$	.49
Attention problems	0.00040	0.00023	$t_{421} = 1.74$	.083
Rule-breaking behavior	−0.00017	0.00037	$t_{426} = -0.47$	.64
Somatic complaints	−0.00032	0.00026	$t_{420} = -1.21$	.23
Social problems	0.00008	0.00031	$t_{418} = 0.26$	.80
Thought problems	−0.00007	0.00028	$t_{422} = -0.24$	.81
Withdrawn/depressed	−0.00005	0.00024	$t_{419} = -0.22$	.83
Series Type, Compared With Rest				
Movie	−0.0002	0.0017	$t_{2235} = -0.09$	.93
Peer	−0.0011	0.0017	$t_{2231} = -0.68$	.50
Age	−0.011	0.0021	$t_{435} = -5.41$	$<10^{-6}$[a]
Sex, Female	−0.0086	0.0036	$t_{422} = -2.39$	.017[a]
IQ	−0.0033	0.0012	$t_{425} = -2.78$	.0056[a]
Barratt Total Score	−0.0012	0.0023	$t_{420} = -0.54$	.59
Highest Parental Education	0.0010	0.0022	$t_{422} = 0.44$	.66
Body Mass Index	−0.0050	0.0017	$t_{417} = -3.01$	.0028[a]

CBCL, Child Behavior Checklist.

[a]Indicates *p* value significant at .05 threshold.

included neurodevelopmental disorders. Across models, the confirmatory sample showed a strong positive association between neurodevelopmental disorders, particularly ASD, and head motion, which was not present in the discovery sample. Because stereotyped and repetitive motor movements are symptoms of ASD, it is not surprising that this population shows greater movement than non-ASD peers (50).

Furthermore, we found consistent evidence across samples of an age × neurodevelopmental disorder interaction: Whereas

Table 5. Fixed Effects From the Linear Mixed-Effects Model Examining Associations Between Head Motion During Functional Magnetic Resonance Imaging, Diagnosis Categories, and Their Interactions With Age, Series Type, and Demographic and Cognitive Covariates

	Standardized Estimate	Standard Error	*t* Statistic	*p* Value
(Intercept)	0.076	0.0042	$t_{480} = 17.85$	$<10^{-15}$[a]
Neuropsychiatric Diagnosis Categories				
Internalizing	−0.0038	0.0034	$t_{422} = -1.12$	.26
Externalizing	0.00020	0.0037	$t_{421} = 0.06$	.96
Neurodevelopmental	0.0079	0.0034	$t_{422} = 2.31$	.021[a]
Neuropsychiatric Diagnosis Categories × Age Interactions				
Internalizing	−0.00069	0.0042	$t_{427} = -0.17$	.87
Externalizing	−0.0012	0.0044	$t_{425} = -0.28$	.78
Neurodevelopmental	0.010	0.0041	$t_{428} = 2.48$	.014[a]
Series Type, Compared With Rest				
Movie	−0.00067	0.0017	$t_{2153} = -0.39$	.70
Peer	−0.00057	0.0017	$t_{2150} = -0.34$	.74
Age	−0.015	0.0045	$t_{424} = -3.34$	.00091[a]
Sex, Female	−0.0045	0.0018	$t_{426} = -2.45$	.051
IQ	−0.0031	0.0012	$t_{950} = -2.61$	.015[a]
Barratt Total Score	−0.0015	0.0023	$t_{422} = -0.65$	.52
Highest Parental Education	0.00084	0.0022	$t_{423} = 0.38$	.71
Body Mass Index	−0.0053	0.0017	$t_{417} = -3.16$	.0017[a]

[a]Indicates *p* value significant at .05 threshold.

our analyses confirmed previous findings that head motion decreases with age, this association was weakened or reversed in children with a neurodevelopmental disorder. Neurodevelopmental disorders are characterized by deficits that occur early in development such that key skills or abilities are inadequately acquired. Voluntary motor control, typically achieved in successive developmental milestones, represents one of the domains wherein such deficits may be expressed (51). Increased head movement may be related to inadequately developed motor control in this group.

Covariates

Older age was significantly associated with reduced head motion across models and samples, consistent with the literature (3–6). Higher age-adjusted BMI was associated with reduced head motion across models in both samples, which was the opposite of previous literature in both children and adults (4,30–32). Our findings may be partially due to the wider age range in our pediatric sample (5–21 years) than that used in previous studies (8–10 years) (4). Additionally, our samples had a mean BMI within 1 SD of the age-adjusted mean, whereas many of the previous studies focused on individuals who were overweight or obese (mean BMI $>$1 SD above the population mean); the true association between BMI and head motion may be nonlinear.

Female sex was associated with reduced head motion in some, but not all, models in both samples. We also did not find consistent support for differences in head motion across fMRI run type or by SES. Higher IQ was associated with reduced head motion in several models but not when the sample was stratified by ADHD diagnosis. This inverse association between IQ and head motion corroborates previous findings (9,29), suggesting that participants with higher IQs were better at following in-scanner instructions to remain still.

Limitations and Future Directions

One major limitation of this study is the high prevalence of ADHD in this sample, which hindered the evaluation of the effects of other disorders. We addressed this by splitting the sample based on ADHD diagnosis (hypotheses 3 and 4). However, future work with a different sample with a more population-representative prevalence of ADHD may be better able to evaluate associations between head motion and other disorders. Furthermore, given the high rates of comorbidity between ADHD and other potentially head motion–relevant diagnoses such as ASD, conclusions based on diagnoses, rather than on symptoms, should be interpreted with caution.

Another limitation that might have reduced replicability is that the samples were recruited at different timepoints. Notably, our confirmatory sample included release 9.0 (December 2020) and release 10.0 (April 2022) data, which included protocols modified due to the COVID-19 pandemic. Additionally, youths recruited before and after the COVID-19–related lockdowns and the caregivers who provided the caregiver-report measures may have been affected in ways not explicitly captured in these study measures. For example, caregivers might have spent more time with their children during the lockdowns and had more opportunity to observe symptoms, or children's social development might have been impacted by the shutdowns of in-person schools and childcare centers. Future work performed on samples collected entirely post-COVID-19 may have better replicability.

A possible explanation for the lack of replicability between the discovery and confirmatory analyses was the smaller size of the latter sample. This suggests that the effect size of any potential true association between head motion and diagnoses may be too small to be of practical significance when designing study protocols. Instead, researchers should be mindful of head motion in all young participants. However, given the potential changes mentioned above in participants and their caregiver reports due to COVID-19, this conclusion should be held tentatively.

In addition to sample size, significant differences in certain participant characteristics were noted between the test and replication samples. However, it is not anticipated that these small mean differences would account for different associations with head motion.

An additional limitation is that this study used percentage of outlier frames as the metric of head motion during fMRI. We used this metric because it was calculated by the HBN QA process and available without downloading raw imaging data. However, this summary statistic about head motion masks potentially relevant details such as the magnitude of head movements. Participants with several large movements may have poorer data quality than participants with several smaller, but still suprathreshold, movements despite both having the same percentage of frames excluded. Future work that examines how neuropsychiatric diagnoses differentially associate with different patterns or types of head motion could be illuminating.

The study is also limited by not the fact that we did not control for medication status. Medications used to treat neuropsychiatric disorders can affect general physical activity and potentially head motion. The HBN provides a medication list for each participant that could be controlled for in future work.

Conclusions

Head motion during fMRI remains a critical confounding factor that may be systematically associated with pediatric neuropsychiatric symptoms such as attention problems or diagnoses such as neurodevelopmental disorders, but such associations are unlikely to be simple and may interact with other diagnoses, age, sex, or other factors. A better understanding of these complex associations may help identify potential confounding factors in imaging studies that involve participants across disorders but will require large sample sizes to address interindividual heterogeneity. Improving our understanding of these associations may also help guide researchers in estimating motion-related data exclusions to ensure adequate sampling during the design of future studies. Furthermore, future work may examine the relative effects of motion-reducing strategies such as mock scanning in different populations of children. For example, given our findings that children with neurodevelopmental disorders had a reduced age-related decrease in head motion, studies of older children with these disorders may benefit from more mock scanning than would be used in a neurotypical population of the same age. In drawing conclusions about developmental populations, psychiatric and cognitive neuroscience research using fMRI

must properly account for how individual variations in symptoms may impact fMRI findings by affecting head motion.

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ARTICLE INFORMATION

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