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How does SES influence the brain circuitry for literacy? Modeling the association between SES, oral language, white matter integrity, and reading

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ABSTRACT

Reading is pivotal for educational and occupational success, hence, understanding the factors contributing to reading skill variation is a major educational objective. Although cognitive and neurobiological factors that influence reading are well documented, the contributions of environmental factors, such as socioeconomic status (SES), fiv to reading-related neurobiology are relatively understudied. Studies have shown that SES predicts reading and the integrity of reading-related white matter tracts; however, the direct and indirect contributions of SES to reading via white matter integrity remain undifferentiated. Further, while oral language (both phonological awareness [PA] and vocabulary) has been positively associated with both SES and reading, only a few studies have attempted to model the SES-reading association via oral language, and none of them included white matter integrity. The current study closes these gaps by using Structural Equation Modeling in a large sample of children from the Healthy Brain Network biobank, testing the (in)direct paths by which SES (parental education) influences reading through oral language and white matter integrity. Results reveal an effect of SES on reading that is indirectly affected by oral language, though not by white matter integrity. These findings reinforce the role of oral language skills as a key pathway linking SES and reading.

1. Introduction

Reading is pivotal for educational and occupational success in modern society, therefore, understanding the factors that contribute to variation in reading skill is a major educational objective. Research on individual differences in reading development reveals a complex multifactorial etiology, encompassing both individual-level and environmental-level contributors to reading skill variation (Pennington, 2006; van Bergen et al., 2014; Andreola et al., 2021). While extensive literature has documented how individual-level cognitive and linguistic capacities relate to neurobiological substrates of reading, considerably less attention has been directed toward examining how environmental factors influence the brain mechanisms that support reading acquisition and proficiency.

Socioeconomic status (SES)—a construct that categorizes individuals based on education, income, and occupational prestige—represents one of the most widely studied environmental factors associated with academic performance in general and reading achievement specifically (e.g., Mascheretti et al., 2018; Theodoridou et al., 2021). SES is most commonly indexed as parental education, or by a composite that includes parental education, given the relative stability of parental education over time and the robust associations between parental education and parent-child interactions (Duncan & Magnuson, 2012; Lewis & Mayes, 2012). Research around the globe has demonstrated robust correlations between SES and both word-level reading and reading comprehension (Buckingham et al., 2013; Dolean et al., 2019; Mascheretti et al., 2018; Sirin, 2005). Moreover, children from lower-SES backgrounds exhibit reduced phonological awareness

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(McDowell et al., 2007; Raz and Bryant, 1990) and more limited vocabularies (e.g., Deutsch and Katz., 1968; Fernald et al., 2013) – both skills that strongly predict early reading development (*e.g.,* Catts et al., 2001; Castles and Coltheart, 2004; Hogan et al., 2005; Hulme and Snowling, 1992; Hulme et al., 2002; Kim et al., 2014; Ouellette, 2006; Ricketts et al., 2007; Wagner, 1997). Given that oral language skills develop prior to reading acquisition, and are correlated with reading proficiency (*e.g.,* Catts et al., 2001; Hogan et al., 2005; Kim et al., 2014; Ouellette, 2006; Wagner et al., 1997), researchers have proposed that SES influences reading development primarily through its impact on oral language development. Indeed, one study of Chinese children found that preschool vocabulary and phonological awareness fully mediated the association between SES and character (word level) reading measured at Grade 3 (Zhang et al., 2013). The association between SES and oral language development likely originates from SES-associated differences in exposure to spoken and written language at home and in the quality of formal early educational experiences (Hart and Risley, 1995; Hoff, 2006; Neuman et al., 2018; Piot et al., 2021; Raz and Bryant, 1990). These findings reveal robust effects of SES on oral language and reading across multiple cultural contexts, with initial evidence from one study suggesting that oral language skills mediate the relationship between SES and reading.

While SES and associated variations in linguistic and educational environments are presumed to influence language and reading development through experience-dependent neuroplasticity, studies of the association between SES, brain structure, and reading proficiency remain limited. Correlational studies of SES and gray matter volume have reported positive associations between SES and volume in brain regions supporting reading and language processing, including the superior temporal gyrus (STG), inferior frontal gyrus (IFG), inferior temporal cortex (ITC), and supramarginal gyrus (SMG) (e.g., Noble et al., 2015; Brito and Noble, 2018; Rakesh and Whittle, 2021). Further, one study by Hair and colleagues (2015) found that frontal and temporal lobe volumes mediated the association between SES and academic skills, including word reading and passage comprehension; they report that gray matter volume in these regions explained up to 20 % of the academic underachievement observed in children from low-income backgrounds.

With respect to white matter, which also exhibits experience-dependent plasticity (Noppeney et al., 2005), a handful of studies have found positive correlations between white matter integrity (measured as fractional anisotropy (FA)) and SES in tracts that have separately been shown to support reading. These include the bilateral superior longitudinal fasciculi (SLF), the bilateral inferior frontal occipital fasciculi (IFOF), the bilateral arcuate fasciculi (AF), and the bilateral inferior longitudinal fasciculus (ILF) (Vanderauwera et al., 2019; Turesky et al., 2022; Rosen et al., 2018; Su et al., 2020; Roy et al., 2024b). In addition, five studies have explored bivariate associations and interactions among SES, word level reading, and white matter integrity within the same sample. Ozernov-Palchik et al., (2019) found that white matter integrity of the bilateral ILF in kindergarten positively predicted second grade reading skill for children from low-SES homes but not for children from high-SES homes, potentially suggesting larger environmental influences on the brain basis for reading among children from lower SES homes. In a subset of children from the same sample who were identified as at-risk for reading difficulties, Zuk et al. (2021) found that both SES and white matter integrity of the right SLF were positively correlated with second grade reading skill, suggesting that integrity in the right SLF and higher SES may serve as protective factors for reading. In a sample of older children (ages 8–14), Gullick et al., (2016) found that reading was positively correlated with white matter integrity in several tracts that have previously been implicated in reading (i.e., left SLF, right ILF, bilateral IFOF) and in the bilateral corticospinal tract (CST); and that SES was positively correlated with integrity in the left CST, right anterior IFOF, left SLF and left temporal ILF. By looking at subgroups of lower and higher SES children they further found two dissociations. The first was found across many of the reading associated regions (left ILF, SLF, CST, and right anterior IFOF) where they observed a positive correlation between reading and FA for higher SES children and a negative correlation for lower SES children. The second dissociation was observed in two of the SES associated regions (right ILF, right inferior IFOF) where they observed a negative correlation for higher SES children and a positive correlation for lower SES children. While these findings are difficult to interpret, especially given no correlation between reading and SES in their study, the authors suggest that they could be driven by differences in home environment and/or instructional emphasis used with the two groups such that tracts related to visual processing (right anterior IFOF, right ILF) might play a more important role in reading for lower SES children and those linked with language processing (left SLF, left ILF) for higher SES children.

Two of the five studies examining white matter, reading, and SES were conducted outside of the US. In a sample of Dutch adolescents, Vanderauwera et al. (2019) found that white matter integrity of the left dorsal AF and ventral Uncinate Fasciculus (UF) positively correlated with both reading and SES. While the uncinate is less commonly linked to either reading or SES, some other studies have found these associations (e.g., Dufford et al., 2017; Koirala et al., 2021; Lichtin et al., 2020; Ozernov-Palchik et al., 2019) and the arcuate has been repeatedly associated with both reading and SES (e.g., Huber et al., 2018; Koirala et al., 2021; Roy et al., 2024a; Wang et al., 2017; Yeatman et al., 2011; Yeatman et al., 2012). Finally, in a sample of Chinese adolescents, Su et al. (2020), found that integrity of the left IFOF positively predicted SES, and that integrity of the left AF positively correlated with age of literacy exposure, vocabulary growth, and their interaction. Dividing the sample by earlier and later literacy exposure revealed a positive association between FA in the AF and vocabulary growth for the children with later literacy exposure, and no association for the early exposure group. These findings held across levels of SES. The authors interpret these findings to suggest that children with later literacy exposure and low vocabulary growth are particularly at risk for low FA in the AF – a key reading associated tract.

Collectively, studies of white matter, reading, and SES have been conducted across three continents and cover a wide range of ages and analytic approaches; however, there is some consistency in the tracts found to be associated with SES and reading across these studies, with the ILF, SLF, IFOF and AF positively correlated with reading *and* SES in more than one study. Broadening to all studies that have examined reading-white matter associations *or* SES-white matter associations, expands the set of tracts identified as correlated with both SES *and* reading in more than one study to include the UF, and the CST (See Supplementary Tables 1 and 2 for a detailed breakdown).

Despite laying an important foundation for understanding the neural basis of SES-reading associations, existing studies linking SES and reading via white matter integrity have several important limitations. First, none explicitly delineate the direct versus indirect effects of white matter in the SES-reading association. This is an important step to identify potential mediators that can explain how SES influences reading. Relatedly, with the exception of Su et al. (2020) extant studies do not consider oral language skill as another pathway from SES to reading. Including oral language in the same model with SES, reading, and white matter integrity is another important step toward identifying causal models. Third, these studies all employ Diffusion Tensor Imaging (DTI), a standard technique in white matter imaging, which is sensitive but not specific to different tissue properties. Newer methods which provide greater specificity (i.e., that implicate orientation *or* density of fibers as determinants of integrity; Zhang et al., 2012) could further specify causal models. And, finally, existing studies have relatively small, racially and ethnically homogenous samples that lean toward higher SES (i.e., parents with post-secondary education, see Supplementary Table 1). They also test narrow age bands that differ markedly across studies from preschool to adolescence, making cross study comparisons difficult. Thus, larger and more diverse samples in terms of SES, race/ethnicity and age are needed to establish generalizability of findings.

The current study addresses these gaps by investigating whether white matter integrity of the tracts most consistently associated with both reading and SES (the bilateral ILF, SLF, IFOF, left AF and UF, and right CST) mediates the association between SES and reading in a much larger and more diverse sample. Additionally, we test whether oral language skills (phonological awareness and vocabulary) constitute part of the indirect pathway between white matter integrity and reading ability. To carry out our study, we utilized the Healthy Brain Network (HBN) biobank of children and adolescents (n = 3101 total at the time of our analysis, 838 with complete white matter data). Based on previous literature that considers white matter, reading, and SES in the same sample, we hypothesized a positive indirect effect of SES (measured as parental education) on reading ability that is mediated in parallel by white matter integrity and oral language skills (phonological awareness and vocabulary). We also predict direct positive associations between: SES and reading, SES and white matter integrity, white matter integrity and oral language, and white matter integrity and reading.

We also take advantage of the wide age range in the HBN dataset to evaluate whether the measured effects of SES on white matter integrity and reading vary by age. Since environmental influences on certain phenotypes diminish with age (Bouchard, 2013; Coyle et al., 2023), we hypothesized that the association between SES and reading (as well as the indirect pathways) would be weaker for older children than for younger ones.

Finally, given recent advances in diffusion MRI analysis methods, we take advantage of models that are more specific to white matter microarchitectural features than traditional tensor-based models (i.e., NODDI [Neurite Orientation Dispersion and Density Imaging]; Zhang et al., 2012). These models measure diffusion in distinct tissue compartments to determine the distribution of fibers within voxels and provide a Neurite Density Index (NDI) and an Orientation Dispersion Index (ODI). These indices are expected to have differential sensitivity to individual variation in reading compared to traditional diffusion measures (e.g., FA), as demonstrated in recent studies (e.g., Koirala et al., 2021; Meisler and Gabrieli, 2022a, 2022b). Thus, we extracted these metrics and hypothesized that ODI and NDI might serve as stronger predictors of reading ability. This would be evidenced by models incorporating these measures explaining a greater proportion of variance or explaining variance with higher statistical confidence (relative to FA) for the overall indirect effect from SES to reading via white matter integrity and oral language skills.

2. Method

2.1. Preregistration

The study was preregistered and is available online at the Open Science Framework (https://osf.io/mpnkg). Four deviations from the preregistered proposal were taken. First, the neural metrics (FA, ODI, and NDI, as well as Contrast to Noise Ratio; CNR, see below) were rescaled using the scale() function in R to avoid estimation problems caused by the values of these metrics being near-zero. Second, correlations between tracts were included as a respecification to improve model fits, given the correlated nature of integrity among the tracts. This also acknowledges important structural relations, as these tracts share biological constraints. Third, an expanded review of the literature, including several newly published findings, revealed more tracts that have been associated with reading and SES in more than one sample, thus we increased the set of included white matter tracts from 4 to 9. Fourth, we included vocabulary as a secondary metric of oral language to be a parallel mediator with PA.

2.2. Participants

Data for the current study includes 3101 children (Age 6–15 years; Mean Age= 9.69 ± 2.35; Females=1107) from the Child Mind Institute (CMI) Healthy Brain Network (HBN) biobank (Alexander et al., 2017).

4873 participants from the CMI-HBN biobank were considered, and five exclusion criteria were applied (see Fig. 1 for a graphic of exclusion criteria application). Participants were excluded if: 1) they had a full-scale IQ below or equal to 70[1] or lacked IQ testing to ensure participants understood testing instructions and therefore had valid assessment; 2) they had a diagnosis of intellectual disability[2] (N = 665 +44 =709); 3) they were younger than six years of age (i.e., could not be adequately assessed with validated measures), or older than fifteen years of age to ensure comparison with existing literature which focuses on younger children (N = 621); 4) they did not have SES data (N = 211); 5) they had incomplete diffusion imaging, reading assessments, *and* oral language assessments (N = 231; participants with partially missing data were included in analysis as described in detail below). The final sample is detailed in Supplementary Tables 3A-B and 4.

Overall, only 806 participants had complete white matter, reading and oral language data. White matter was the variable most affected by missingness; only 1256 participants (∼ 40 %) of the sample had diffusion data for at least one out of nine tracts, and only 838 participants had complete cases for the nine tracts. Missingness for all endogenous variables and one exogenous variable (average CNR, i.e., the MRI scan quality metric), was handled with the Full Information Maximum Likelihood (FIML) method (Allison, 2012; Enders, 2023), which estimates overall model parameters using available variables, rather than imputing and replacing individual missing values. A set of sensitivity analyses were performed by fitting the three (FA, ODI, and NDI) models using the subsample (n = 838) with complete cases for the nine tracts (but some [<10 %] missingness for the other endogenous variables). This step was performed to test whether model results would hold after removing the large number of participants with incomplete white matter data.

2.3. Procedures and materials

Participants and their families underwent extensive testing to be included in the HBN biobank; this includes a whole-brain MRI protocol, a comprehensive neuropsychological battery, and a series of questionnaires filled out by parents (Alexander et al., 2017).

2.3.1. Behavioral and questionnaire data

Demographic Information. Age and sex assigned at birth were included in the models as covariates.

Measure of SES. The parental education composite score of the Barratt Simplified Measure of Social Status BSMSS Questionnaire (Barratt, 2006) was taken as a measure of SES. Parental education was chosen because it is thought to be a stable metric of SES (Duncan & Magnuson, 2012; Lewis & Mayes, 2012) and because this question was answered by most participants in the sample and checked for reliability. For this measure, each parent is given a score, which ranges from 3 to 21, in three-point increments, based on the level of education achieved

[1] Assessed with the Wechsler Intelligence Scale for Children V (WISC - Wechsler, 2014), the Wechsler Abbreviated Scale of Intelligence II (WASI - Wechsler, 2008), or the Kaufman Brief Intelligence Test II (KBIT – Kaufman and Kaufman, 2004).

[2] Children were evaluated by licensed clinicians with Kaufman Schedule for Affective Disorders and Schizophrenia—Children's version (KSADS; Kaufman, 1997), a semi-structured DSM-5-based psychiatric interview. The interview was reviewed together with all materials collected during study participation and used to derive clinical diagnoses (Alexander et al., 2017).

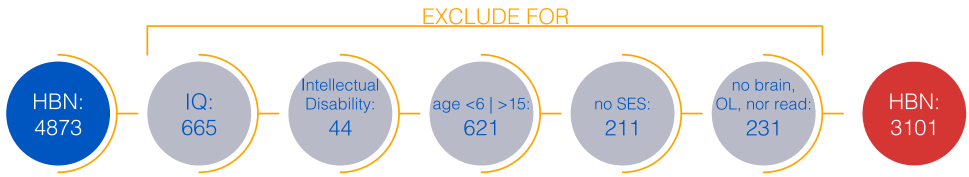

Fig. 1. Exclusion Criteria. Schematic representation of the application of exclusion criteria. 4873 participants from the Healthy Brain Network biobank were considered. After applying exclusion criteria, the sample size reduced to 3101. OL= Oral Language (PA and vocabulary knowledge were considered).

by the parent; the composite score is obtained by averaging the scores of parent 1 (P1) and parent 2 (P2).[3] In this study, the parental education composite score was centered using the *scale()* function in base R to increase numerical stability.

2.3.2. Measures of oral language and Reading

Phonological Awareness. The raw scores of the Comprehensive Test of Phonological Processing 2 (CTOPP-2; Wagner et al., 2013) Blending Words (BW) and Elision (EL) subscales were centered and scaled using the *scale()* function in base R (to create z-scores to account for differences in the subtests' scales), and averaged to create a composite score of phonological processing.[4] The EL subtest comprises 34 items for which the participant is asked to listen to a word and then repeat it without a designated sound (*e.g.,* "now say bold without saying /b/", where the expected response is "old"). The BW subtest comprises 33 items for which the participant is asked to listen to a series of recorded, separate sounds, and is asked to blend them together to form a word (*e.g.,* "what word do these sounds make: t-oi?", where the expected response is "toy").

Vocabulary. The raw scores of the Wechsler Intelligence Scale's (Wechsler Intelligence Scale for Children V - WISC; Wechsler, 2014; or the Wechsler Abbreviated Scale of Intelligence II - WASI; Wechsler, 2008) Vocabulary subtest were centered and scaled using the *scale()* function in base R to create our measure of Vocabulary. In these assessments, the participant must provide the names for pictures and define words presented orally or in print.

Measure of Reading. The raw scores of the Test of Word Reading Efficiency, 2nd Edition TOWRE-2 (Torgesen et al., 2012) Sight Word Efficiency (SWE) and Phonemic Decoding Efficiency (PDE) subscales were centered and scaled using the *scale()* function in base R (to create z-scores to account for differences in the subtests' scales), and averaged to create a composite score of reading skills[5]. The SWE subtest contains a list of 108 printed words which the participant is asked to read out loud; the administrator identifies how many words the participant has read accurately within the first 45 seconds. The PDE subtest contains a list of 66 printed phonemically regular nonwords which the participant is asked to read out loud; the administrator identifies how many words the participant has read accurately within the first 45 seconds.

2.3.3. MRI data acquisition and processing

All raw MRI data (anatomical MPRAGE-T1w and diffusion-weighted images, dMRI) were downloaded in BIDS format from an open access database (Healthy Brain Network), the details of which can be found elsewhere (Alexander et al., 2017). These scans were acquired using 3 Tesla scanners, with the data acquisition procedure approved by the Chesapeake Institutional Review Board (https://www.chesapeakeirb.com/). The dMRI data for all participants were first subjected to a quality control algorithm, using an automated quality control framework (QUAD -Quality Assessment for dMRI; Bastiani et al., 2019) available as an open-source toolbox in FSL (ver. 6.0.3), to compute image quality metrics which were used as a proxy for typical visual inspection of dMRI scans. The computed Contrast to Noise ratio (CNR) was then used in the models as a metric of dMRI image quality.

To obtain the diffusion and tract measures, the images were preprocessed using inbuilt functionality in FSL, as described in detail elsewhere (Behrens et al., 2007; Jenkinson and Smith, 2001; Koirala et al., 2018, Koirala et al., 2022). In brief, after preprocessing - correction for susceptibility-induced artifacts (Andersson et al., 2003; Smith et al., 2004), and motion artifacts (eddy currents and head movements) (Andersson & Sotiropoulos, 2016), as well as brain extraction (Smith, 2002) - a diffusion tensor model was fitted to each voxel to obtain Fractional Anisotropy (FA) using the FDT toolbox in FSL. In addition, the distribution of crossing fibers was estimated using BEDPOSTX (Behrens et al., 2007; Behrens et al., 2003), and the probability of major (f1) and secondary (f2) fiber directions were calculated (Koirala et al., 2017; Koirala et al., 2019). The obtained crossing fiber-modeled diffusion data were further processed using the automatic tractography scheme with the XTRACT toolbox in FSL (Warrington et al., 2020). The resultant tracts were then stored in standard space and overlaid on the FSL_HCP1065 FA atlas (Warrington et al., 2020).

Additionally, the neurite orientation dispersion and density imaging (NODDI) model was applied to obtain more specific indices of tissue properties, including the neurite density index (NDI) and the orientation dispersion index (ODI). The NODDI model takes advantage of diffusion MRI acquisitions with multiple diffusion weightings (*b*-values) and a greater number of gradient directions (>30) to model diffusion in distinct tissue compartments (intra-cellular vs. extra-cellular). Details on how these measures are obtained for each tract are described elsewhere in detail (e.g., Koirala et al., 2021; Pierpaoli et al., 1996, Beaulieu, 2002, Jones et al., 2013; Zhang et al., 2012; Zhang et al., 2011).

For both FA and NODDI metrics, we included the nine tracts most robustly associated to both reading and SES (see Supplementary Table 2 for an overview of the literature): the bilateral ILF, SLF, IFOF, and the left AF and UF, and the right CST (Fig. 2). Each brain metric (average CNR, FA, ODI, and NDI) was centered and scaled using the *scale()* function in base R (to create z-scores) to increase numerical stability and

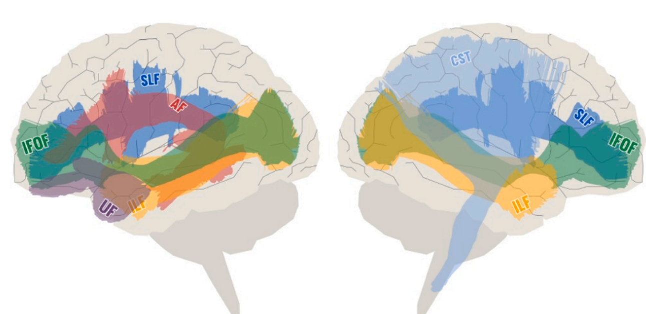

Fig. 2. Schematic of the white matter tracts included. In blue the Superior Longitudinal Fasciculus (SLF), in yellow the Inferior Longitudinal Fasciculus ILF), in green the Inferior Frontal Occipital Fasciculus (IFOF), in red the Arcuate Fasciculus (AF), in purple the Uncinate Fasciculus (UF), and in light blue the CorticoSpinal Tract (CST).

[3] In the case of single-parent families, the single datapoint provided was used.

[4] Raw scores were preferred over publisher-standardized scores as the purpose of this study was to examine how individual performance on PA/reading relates to other variables not how performance-relative-to-peers relates to other variables.

precision before the mediation analysis.

2.4. Structural equation modeling

Structural Equation Modeling (SEM) was used to fit path models of SES on reading (see Fig. 3 for a schematic) as implemented in the Mplus 8.1 software package (Muthén and Muthén, 2017). SEM is a regression-based family of techniques that allows for simultaneous modeling of the complex associations among a system's variables (McCoach and Cintron, 2021). By accounting for measurement error, SEM produces unbiased estimates (compared to more traditional tests based on sequential regressions; McCoach and Cintron, 2021) for the direct effects of predictors on the predicted variable (*i.e.,* the effect explained by the predictor alone), the specific indirect effects (*i.e.,* all those effects from a predictor to the predicted variable that are routed through one or more mediators), the total indirect effect (*i.e.,* the cumulative effect from a predictor to the predicted variable that are routed through all possible mediators), and the total effect (*i.e.,* the combination of the direct and total indirect effects).

All models included SES as the predictor of interest, three predictors used to account for possible effects of age, sex assigned at birth, and MRI image quality (*i.e.,* Contrast to Noise Ratio, CNR), and a predictor that modeled the interaction of SES and age to test how the paths' effects change as a function of age.

White matter integrity for the bilateral ILF, SLF, IFOF, the left AF and UF, and the right CST were used as parallel mediators and were correlated with each other to capture the variance they share as part of one common organ (*i.e.,* the brain); Fractional Anisotropy (FA), Orientation Dispersion Index (ODI), and Neurite Density Index (NDI) were used as metrics of white matter integrity in separate models. That is, we ran one model for each white matter integrity metric (3 total models, not counting the sensitivity analysis [discussed below]).

PA and vocabulary were included as serial mediators with white matter integrity (*i.e.,* the effects of SES on reading would be serially mediated by first white matter, and then by PA and vocabulary). PA and vocabulary were parallel mediators and were allowed to correlate. Finally, reading was used as the dependent variable (Fig. 4).

Sensitivity Analyses. Given the large number of participants with missing white matter data we re-fit all the three (FA, ODI, and NDI) models including only participants with white matter data for all nine

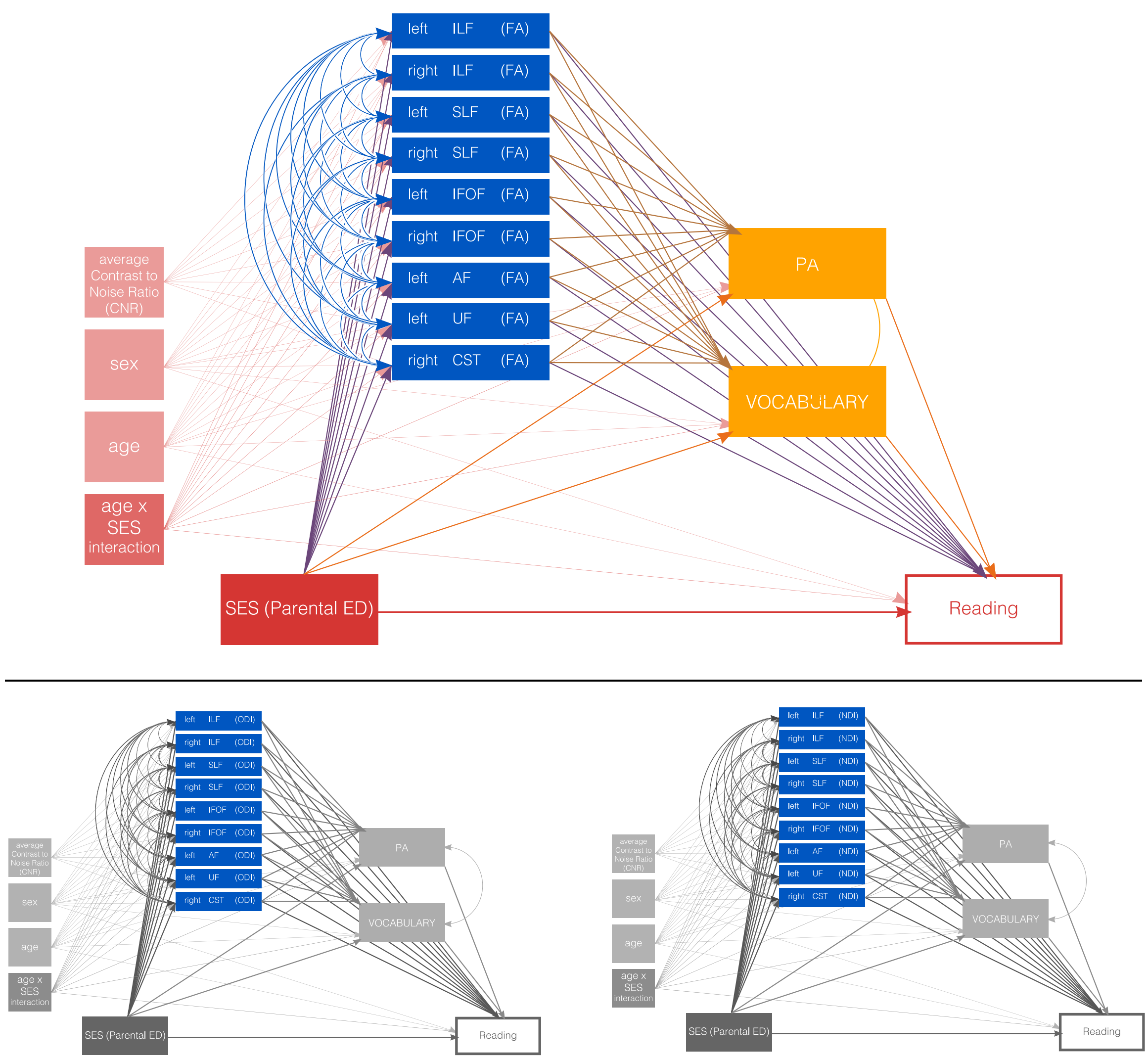

Fig. 3. Schematic of the models tested. At the top, the path diagram of the tested model for Fractional Anisotropy, at the bottom, from left to right, the path diagrams for Orientation Dispersion Index and Neurite Density Index. In each path diagram, the boxes indicate the predictor (SES, solid red) and the predicted (reading, outlined red) variables, the control predictors (age, sex assigned at birth, and contrast-to-noise-ration, in light pink), the ageXses interaction term (in dark pink), and the mediators (the white matter metrics for the nine tracts in blue and PA in yellow). One sided arrows indicate paths from one predictor to its predicted variable, and double-sided arrows indicate correlations. Different colors have been used to highlight the different paths (e.g., purple paths go from SES to reading via white matter integrity, while orange paths go from SES to reading via PA). The three models differ only by the white matter integrity metric used.

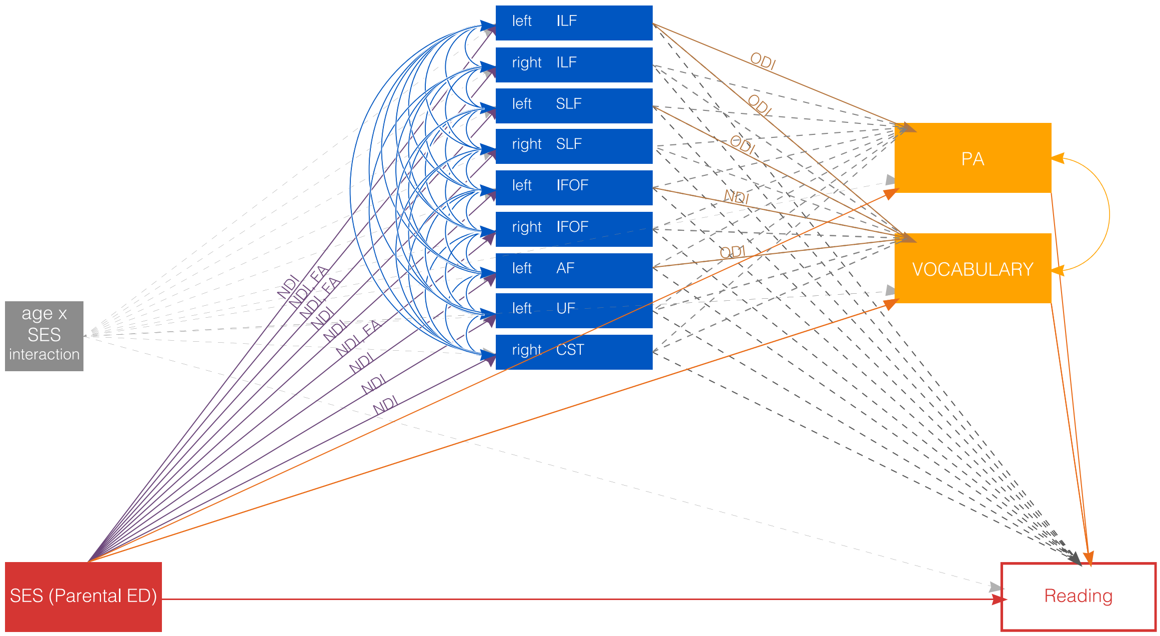

Fig. 4. Schematic of model structure and overall results (full model; n = 3101). Solid lines represent paths which are statistically significant at the 95 %CI, while dashed/grayed-out lines represent paths which did not meet this level of statistical significance. For the paths to and from the neural metrics, the metric for which each path is statistically significant is indicated.

tracts. (N = 838). A full description of this subsample (Supplementary Tables 8A-B) and complete results of this analysis (Supplementary Tables 9–11) can be found in the supplementary material.

3. Results

3.1. Fractional anisotropy model

The model yielded good fit ($\chi^2(7)$=5.814, p = .562; CFI=1; RMSEA<.001 90 %C.I. [000–.020]; SRMR=.008). Below are reported total, total indirect, specific indirect, and direct effects for all variables for which the influence on reading was tested. See supplementary Tables 5A-B for a summary of the FA model estimates. See Table 1A-B for a selected summary of the FA model effects and path estimates. A full summary is provided in Supplementary Tables 5A-B.

SES on Reading. Our model revealed a total effect of parental education (*i.e.,* SES) on reading (β=.195, 95 % C.I.[.165,.222]), which is made up of a total indirect effect (sum of all specific indirect effects; total indirect β=.145, 95 % C.I.[.128,.164]) and a direct effect (from SES to reading (β=.050, 95 % C.I.[.024,.074]). Note that the total indirect effect is best characterized by the specific indirect effects of SES on reading via PA (β=.090, 95 % C.I.[.076,.105]) and via Vocabulary (β=.054, 95 % C.I.[.045,.064]); specific indirect effects via brain metrics were not statistically significant. This pattern of effects reveals that SES is positively associated with reading, and that this association is partially explained by oral language. In other words, children from higher SES families tend to perform better on PA and vocabulary, which positively affects their reading performance, resulting in higher reading scores compared to their lower SES peers.

SES by Age Interaction on Reading. There was no SES by age interaction effect on reading at the 95 % CI.

SES on FA. The paths from SES to the right ILF (β=.066, p = .019), the left SLF (β=.059, p = .030), and the right IFOF (β=.064, p = .015) were statistically significant, revealing small effects of SES on white matter integrity. These positive effects reveal that higher SES is associated with greater white matter integrity for these three tracts. No other paths from SES to FA were statistically significant at the 95 % CI.

Oral Language on Reading. The paths from PA (β=.386, p < .001) and vocabulary (β=.217, p < .001) to reading were statistically significant confirming a small effect of oral language on reading. These effects reveal that increased PA and vocabulary are associated with better reading.

FA on Reading. There was no effect of FA on reading at the 95 % C.I.

FA on Oral Language. There was no effect of FA on PA nor Vocabulary at the 95 % C.I.

Table 1
*FA Model Results – Total and Indirect Effects:*Estimates and Confidence Intervals of Standardized Total Effects and Significant (95 %C.I.) Indirect Effects in The Full Model *vs.* The Sensitivity Model.

	Estimate (95 % C.I.) Full (n = 3101)	Estimate (95 % C.I.) Sensitivity (n = 838)
Effects from SES to reading		
Total	0.195 (0.165, 0.222)	0.226 (0.174, 0.268)
Total indirect	0.145 (0.128, 0.164)	0.150 (0.114, 0.177)
Specific indirect via vocabulary	0.054 (0.045, 0.064)	0.055 (0.037, 0.074)
Specific indirect via PA	0.090 (0.076, 0.105)	0.094 (0.068, 0.119)
Direct SES to reading	0.050 (0.024, 0.074)	0.077 (0.032, 0.117)
Effects from SESxAge to reading		
Total	0.013 (n.s.)	−0.012 (n.s.)
Effects from lILF to reading		
Total	0.040 (n.s.)	0.061 (n.s.)
Effects from rILF to reading		
Total	0.013 (n.s.)	−0.024 (n.s.)
Effects from lSLF to reading		
Total	−0.078 (n.s.)	−0.053 (n.s.)
Effects from rSLF to reading		
Total	−0.063 (n.s.)	−0.015 (n.s.)
Effects from lAF to reading		
Total	0.063 (n.s.)	0.014 (n.s.)
Effects from lUF to reading		
Total	0.056 (n.s.)	0.020 (n.s.)
Effects from lIFOF to reading		
Total	0.020 (n.s.)	−0.069 (n.s.)
Effects from rIFOF to reading		
Total	0.015 (n.s.)	0.099 (n.s.)
Effects from rCST to reading		
Total	−0.030 (n.s.)	−0.034 (n.s.)

3.2. Orientation dispersion index model

The model yielded good fit (χ^2(7)=5.874, p = .555; CFI=1; RMSEA=.000 90 %CI [.000–.020]; SRMR=.010). The pattern of significance for the ODI model deviated from that observed for FA in the association between SES and white matter, specifically, no statistically significant effects from SES to any of the tracts were observed at the 95 %CI. Furthermore, the path from left ILF to PA was found to be statistically significant (β=-0.109, p = .016), as well as the paths from the left ILF (β=-0.106, p = .007), the left SLF (β=0.095, p = .043), and the left AF (β=0.033, p = .038) to vocabulary. See Table 2A-B for a selected summary of the ODI model effects and path estimates. A full summary is provided in Supplementary Tables 6A-B.

3.3. Neurite density index model

The model yielded good fit (χ^2(7)=15.170, p = .034; CFI=1; RMSEA=.015 90 %CI [.005–.033]; SRMR=.013). The pattern of significance for the NDI model deviated from that observed for FA, specifically, all paths from SES to the white matter tracts were found to be statistically significant (left ILF: β=.070, p = .005; right ILF: β=.080, p = .001; left SLF: β=.076, p = .002; right SLF: β=.051, p = .041; left IFOF: β=.086, p =.001; right IFOF: β=.080, p = .001; left AF: β=.083, p = .001; left UF: β=.075, p = .004; right CST: β=.087, p = .003) revealing small effects of SES on white matter integrity for this metric. Furthermore, the path from left IFOF to vocabulary was found to be statistically significant (β=-0.033, p = .048). See Table 3A-B for a selected summary of the NDI model effects and path estimates. A full summary is provided in Supplementary Tables 7A-B (Table 4).

3.4. Sensitivity analyses

Many of the results remained unvaried in significance, magnitude, and direction; however, we did observe some differences, all within the white matter paths. Specifically, in the sensitivity analyses, in the FA model, the paths from SES to the right ILF and IFOF and left SLF are no longer statistically significant at the 95 % C.I., and the path from the right IFOF to PA was found to be statistically significant (β=0.128, p = .042). In the ODI model, the path from SES to the left SLF was statistically significant (β=-.062, p = .046), the path from the right IFOF to PA was significant (β=-0.139, p = .017), and a total effect of the left ILF on reading was significant (β=-.083, 95 % C.I.[-.160, −.005]). In the NDI model, none of the paths from SES to the white matter tracts were statistically significant, nor was the path from IFOF to vocabulary. See Tables 1–3 for a selected summary of the FA model effects and path estimates. A full summary is provided in Supplementary Tables 9–11.

Table 2
*FA Model Results – Paths:*Significant (p < 0.05) Standardized Path Estimates in The Full Model *vs.* The Sensitivity Model Results.

	Estimate (p-value) Full (n = 3101)	Estimate (p-value) Sensitivity (n = 838)
Paths to reading		
SES	0.050 (<.001)	0.077 (0.001)
vocabulary	0.217 (<.001)	0.219 (<.001)
PA	0.386 (<.001)	0.395 (<.001)
Paths to PA		
SES	0.232 (<.001)	0.238 (<.001)
rIFOF	0.071 (n.s.)	0.128 (0.042)
Paths to vocabulary		
SES	0.251 (<.001)	0.253 (<.001)
Paths to rILF		
SES	0.066 (0.019)	0.037 (n.s.)
Paths to lSLF		
SES	0.059 (0.030)	0.044 (n.s.)
Paths to rIFOF		
SES	0.064 (0.015)	0.042 (n.s.)

Table 3
ODI Model Results – Total and Indirect Effects:Estimates and Confidence Intervals of Standardized Total Effects and Significant (95 %C.I.) Indirect Effects in The Full Model vs. The Sensitivity Model.

	Estimate (95 % C.I.) Full (n = 3101)	Estimate (95 % C.I.) Sensitivity (n = 838)
Effects from SES to reading		
Total	0.195 (0.165, 0.221)	0.226 (0.173, 0.276)
Total indirect	0.141 (0.125, 0.160)	0.147 (0.112, 0.180)
Specific indirect via vocabulary SES	0.053 (0.044, 0.063)	0.054 (0.035, 0.076)
Specific indirect via PA SES	0.091 (0.077, 0.106)	0.094 (0.067, 0.123)
Direct SES to reading	0.053 (0.027, 0.077)	0.079 (0.034, 0.126)
Effects from SESxAge to reading		
Total	0.013 (n.s.)	−0.012 (n.s.)
Effects from lILF to reading		
Total	−0.077 (n.s.)	−0.083 (−0.16, −0.005)
Total indirect		−0.050 (−0.101, −0.007)
Specific indirect via vocabulary		−0.016 (n.s.)
Specific indirect via PA		−0.033 (n.s.)
Direct to reading		−0.034 (n.s.)
Effects from rILF to reading		
Total	0.042 (n.s.)	0.059 (n.s.)
Effects from lSLF to reading		
Total	0.063 (n.s.)	0.058 (n.s.)
Effects from rSLF to reading		
Total	0.016 (n.s.)	−0.012 (n.s.)
Effects from lAF to reading		
Total	−0.033 (n.s.)	0.011 (n.s.)
Effects from lUF to reading		
Total	−0.039 (n.s.)	−0.007 (n.s.)
Effects from lIFOF to reading		
Total	−0.008 (n.s.)	0.049 (n.s.)
Effects from rIFOF to reading		
Total	−0.028 (n.s.)	−0.092 (n.s.)
Effects from rCST to reading		
Total	−0.001 (n.s.)	0.025 (n.s.)

Table 4
ODI Model Results – Paths:Significant (p < 0.05) Standardized Path Estimates in The Full Model vs. The Sensitivity Model.

	Estimate (p-value) Full (n = 3101)	Estimate (p-value) Sensitivity (n = 838)
Paths to reading		
SES	0.053 (<.001)	0.079 (0.001)
vocabulary	0.211 (<.001)	0.215 (<.001)
PA	0.389 (<.001)	0.396 (<.001)
Paths to PA		
SES	0.233 (<.001)	0.236 (<.001)
lILF	−0.109 (0.016)	−0.084 (0.06)
rIFO	−0.093 (n.s.)	−0.139 (0.017)
Paths to vocabulary		
SES	0.254 (<.001)	0.252 (<.001)
lILF	−0.106 (0.007)	−0.075 (n.s.)
lSLF	0.095 (0.043)	0.045 (n.s.)
lAF	−0.085 (0.038)	−0.011 (n.s.)
Paths to lSLF		
SES	−0.020 (n.s.)	−0.062 (0.046)

Table 5

4. Discussion

In this study, we used SEM to quantitatively test a theoretical model of the direct and indirect pathways from SES (operationalized as

Table 5
NDI Model Results – Total and Indirect Effects:Estimates and Confidence Intervals of Standardized Total Effects and Significant (95 %C.I.) Indirect Effects in The Full Model vs. The Sensitivity Model.

Effects from SES to reading	**Estimate (95 % C.I.) Full (n = 3101)**	**Estimate (95 % C.I.) Sensitivity (n = 838)**
Total	0.195 (0.165, 0.222)	0.226 (0.173, 0.268)
Total indirect	0.143 (0.126, 0.161)	0.149 (0.114, 0.177)
Specific indirect via vocabulary	0.054 (0.044, 0.064)	0.053 (0.035, 0.072)
Specific indirect via PA	0.088 (0.075, 0.104)	0.093 (0.067, 0.118)
Direct SES to reading	0.052 (0.026, 0.076)	0.077 (0.033, 0.119)
Effects from SESxAge to reading		
Total	0.013 (n.s.)	−0.012 (n.s.)
Effects from lILF to reading		
Total	0.045 (n.s.)	0.069 (n.s.)
Effects from rILF to reading		
Total	−0.007 (n.s.)	−0.091 (n.s.)
Effects from lSLF to reading		
Total	−0.043 (n.s.)	−0.027 (n.s.)
Effects from rSLF to reading		
Total	−0.056 (n.s.)	−0.044 (n.s.)
Effects from lAF to reading		
Total	0.094 (n.s.)	0.061 (n.s.)
Effects from lUF to reading		
Total	−0.040 (n.s.)	−0.014 (n.s.)
Effects from lIFOF to reading		
Total	−0.022 (n.s.)	0.008 (n.s.)
Effects from rIFOF to reading		
Total	0.042 (n.s.)	0.071 (n.s.)
Effects from rCST to reading		
Total	−0.024 (n.s.)	−0.011 (n.s.)

Table 6
NDI Model Results – Paths:Significant (p < 0.05) Standardized Path Estimates for The Full Model vs. The Sensitivity Model.

	Estimate (p-value)Full (n = 3101)	**Estimate (p-value) Sensitivity (n = 838)**
Paths to reading		
SES	0.052 (<.001)	0.077 (0.001)
lILF	0.086 (0.047)	0.092 (n.s.)
vocabulary	0.220 (<.001)	0.216 (<.001)
PA	0.390 (<.001)	0.403 (<.001)
Paths to PA		
SES	0.227 (<.001)	0.231 (<.001)
Paths to vocabulary		
SES	0.245 (<.001)	0.247 (<.001)
lIFO	0.138 (0.048)	0.113 (n.s.)
Paths to lILF		
SES	0.070 (0.005)	0.021 (n.s.)
Paths to rILF		
SES	0.080 (0.001)	0.024 (n.s.)
Paths to lSLF		
SES	0.076 (0.002)	0.033 (n.s.)
Paths to rSLF		
SES	0.051 (0.041)	0.007 (n.s.)
Paths to lAF		
SES	0.083 (0.001)	0.031 (n.s.)
Paths to lUF		
SES	0.075 (0.004)	0.031 (n.s.)
Paths to lIFOF		
SES	0.086 (0.001)	0.046 (n.s.)
Paths to rIFOF		
SES	0.080 (0.001)	0.038 (n.s.)
Paths to rCST		
SES	0.087 (0.003)	0.023 (n.s.)

parental education level) to reading via white matter microstructure and oral language. With our approach, we provide six advances beyond the existing literature. First, while five other studies have examined both the association between SES and white matter integrity and between white matter integrity and reading in the same sample (*i.e.,* Vanderauwera et al., 2019; Su et al.,2020; Ozernov-Palchik et al., 2019; Zuk et al., 2021; Gullick et al., 2016), none have attempted to parcel out the direct and indirect effects from SES to reading, considering white matter integrity as a potential mediator. Second, our models included all nine tracts (the bilateral ILF, SLF, and IFOF, the left AF and UF, and the right CST) that had been previously associated with reading and SES in at least two independent studies. Third, considering substantial evidence that PA and vocabulary are influenced by SES and closely related to reading development, we included both oral language measures as potential mediators (parallel to each other and serial to white matter). Fourth, given the large range of ages represented across existing studies of reading, SES, and white matter, as well as findings suggesting that environmental influences on cognition may not be constant across ages (Bouchard, 2013), we included the interaction of age and SES as a predictor in our models. Fifth, in addition to a model with FA (a widely used metric of white matter integrity), we considered recent evidence of differential informativeness of white matter microstructure metrics in explaining the effects of SES on white matter development (Li et al., 2023) and of white matter on reading (Koirala et al., 2021; Meisler and Gabrieli, 2022), and ran two additional models using measures of fiber orientation (ODI) and fiber density (NDI). Sixth, we utilized a large and diverse database of participants, making our sample much larger and more diverse than previous studies that have examined SES, reading, and white matter conjointly. Table 6

4.1. SES influences reading through PA and vocabulary, but not white matter

With respect to our primary hypothesis, we did not find evidence that white matter integrity of any of the nine tracts influenced the association between SES and reading. That is, no specific indirect path from SES to reading involving any of these tracts reached statistical significance. This can be explained by the limited number of significant paths from white matter to reading. A statistically significant indirect effect from SES to reading via white matter can only be observed if each of the paths to and from white matter is statistically significant. In the full sample models, while several paths from SES to white matter were significant (discussed below), only one of these tracts had a statistically significant path to reading (left ILF, NDI model only), and the effect was small (standardized estimate =.086; $p = .047$).

Critically, we found a significant effect of SES on reading that was partially explained by both PA and vocabulary across all models. This is in line with previous studies that have found PA to be a robust predictor of reading development (e.g., Wagner et al., 1997; Hogan et al., 2005; Catts et al., 2001), those that reveal an association between vocabulary and word reading (Ouellette, 2006; Kim et al., 2014), those that reveal an association between SES and PA (e.g., McDowell et al., 2007; Raz and Bryant, 1990), and those that reveal an association between SES and vocabulary (e.g., Fernald et al., 2013). As noted above, the effects of SES on oral language may be driven by SES-related differences in educational opportunity and language exposure (Hoff, 2013; Share et al., 1983; Durham et al., 2007). Educational practices which may be particularly relevant for reading and PA and influenced by SES include home literacy focused activities such as shared book reading (e.g., Turesky et al., 2022). Consistent with this idea, Raz and Bryant (1990) found differences between middle income and lower income children's PA, as well as the number of books present in their homes, and the number of hours their parents spent reading with them.

4.2. SES influences neurite density and FA; neurite density and orientation dispersion influence oral language

Although we found no indirect effect from SES to reading via white matter, in the full sample models we observed several significant paths from SES to white matter, and from white matter to oral language, and one significant path from white matter to reading. Specifically, in the full sample FA model we observed significant paths from SES to the right

ILF, the left SLF, and the right IFOF. In the full sample NDI model, all paths from SES to white matter tracts reached statistical significance, as did the paths from the left ILF to reading and from the left IFOF to vocabulary. Contrary to previous findings, (e.g., Gullick et al., 2016; Huber et al., 2018; Ozernov-Palchik et al., 2019; Su et al.; 2020; Vanderauwera et al., 2019; Wang et al., 2017; Zuk et al., 2021; Yeatman et al., 2012) we did not observe any direct positive associations between FA for any of the nine tracts and reading.

In the ODI model, we observed a significant path from the left ILF and right IFOF to PA. We also observed four statistically significant paths from white matter to vocabulary (the left ILF, left SLF, and left AF in the ODI model, and the left IFOF in the NDI model).

In the sensitivity analyses, most of these were no longer significant. The only confirmed effects in the sensitivity analyses were in the ODI model for paths to oral language (i.e., left ILF to PA; left ILF, left SLF and left AF to vocabulary). Additionally, a few paths were significant in the sensitivity analyses that were not significant in the full sample models, including the right IFOF to PA (FA and ODI models), SES to the left SLF (ODI model), and the total effect of the left ILF on reading (ODI model).[5] We discuss the lack of robust white matter findings below with hypothesis three.

4.3. Age does not affect the association between SES and reading

With respect to our second hypothesis, the total effect for the SES by age interaction term was not statistically significant for any of the three models we tested (neither with the full sample, nor in the sensitivity analyses). This suggests that the association between parental education level and reading in our sample is constant from age 6–15. However, it may still be the case that SES has a greater influence on brain development early in life that was not captured in the age range included in our sample. Future research with a longitudinal design is needed to further investigate this association.

4.4. Weak evidence for greater explanatory power in NODDI models

Regarding our third hypothesis, we found only weak evidence for increased explanatory power for white matter metrics that are more specific to microstructural features. That is, we observed slightly larger effect sizes and some additional high confidence findings in the ODI and NDI models compared to the FA model. For example, the ODI effects (left ILF to PA; left ILF, left SLF, and left AF to vocabulary) were the only white matter associations that were significant in both the full models and subset with full data (sensitivity analyses). These findings could suggest that the orientation of the fibers within a bundle is more likely to influence/be influenced by oral language relative to the density of the fibers. However, given the limited number of paths and effects that reached statistical significance in both the full sample analysis and the sensitivity analyses, this hypothesis was difficult to evaluate.

Regarding the small number of white matter associations that reached statistical significance, we suggest that our findings may approximate the true nature and size of these effects. Ours is the largest sample of white matter-SES and white matter-reading associations to date. This is important, as Marek et al. (2022) demonstrated with their large-scale analysis of Brain Wide Association Studies (BWAS), large samples are needed ($n = 1000+$) to estimate the true effect size for brain-behavior correlations. These authors and others (e.g., Button et al., 2013) further suggest that small samples can lead to spurious correlations. Thus, it may be the case, consistent with Marek et al. (2022), that associations between white matter integrity and reading and between SES and white matter integrity tend to be small, and that the extant literature contains false positives. Indeed, Roy et al. (2024a) found few white matter-reading correlations when they interrogated several large samples.

The HBN sample is also more diverse than most, not just in terms of SES and race, but also in neurodiversity, with many children carrying at least one clinician provided diagnosis (see Supplementary Tables 2 A and 3). While many studies apply strict exclusion criteria concerning the presence of conditions other than dyslexia, we suggest that the HBN sample with its diversity preserved is more representative of the population (see Supplementary 3 for rates of diagnoses in this sample vs. the general US population), and thus findings from this sample should be more generalizable. Notably, while previous studies using the HBN biobank have yielded numerous statistically significant positive associations between white matter and reading (e.g., in the bilateral UF, left AF, ILF, and SLF) when applying strict exclusionary criteria (e.g., Koirala et al., 2021; Meisler & Gabrieli, 2022), few statistically significant associations were observed when the sample's neurodiversity was preserved (e.g., Roy et al., 2024a). Finally, we note that our sample includes a broader age range and older children than most published studies, which may also contribute to differences between our study and others, given rapid changes in synaptic connectivity, pruning, and myelination during childhood (Giedd et al., 1999; Huttenlocher,1979; Dumontheil, 2022).

4.5. Limitations and future directions

The current study should be considered in light of several limitations. The primary limitation of the present approach is the lack of longitudinal data. While the HBN sample is larger and more representative than most, it does not track individual participants over time. Future investigations should ask whether white matter integrity partially explains the effects of SES on reading in a longitudinal context to be able to infer causality. Moreover, while the SES range in the HBN sample is slightly larger than in previous studies of SES, white matter, and reading, it still over represents higher SES children relative to the US population (e.g., 96.7 % of parents in the HBN sample have completed high school vs. 87 % nationally; COE - high school graduation rates, 2024). Finally, future studies could test alternative and more elaborate models. For example, while our approach tests for mediation by white matter and oral language on the SES-reading association, future large-scale studies could test a competing model wherein SES is considered as a moderator for the association between white matter and reading. Moderation effects would be consistent with Ozernov-Palchik et al. (2019) and Gullick et al. (2016), who, as discussed above, found opposing patterns of reading-white matter associations for low vs. high SES children (see also Farah et al., 2017 for a discussion of moderation effects involving SES). Likewise, given the wide reaching influence of SES, future studies could include additional environment-level and/or individual-level mediators or moderators, and could go beyond single word reading to consider reading comprehension as an outcome of interest.

5. Conclusion

In conclusion, we did not find evidence for indirect effects from SES to reading via white matter integrity in any of nine tracts that have previously been associated with both SES and reading in more than one independent sample. However, our study does corroborate some effects previously described in the literature in a larger and more diverse sample than most. Importantly, we confirmed the effect of SES on reading in our sample and showed that this effect is partially explained by PA and vocabulary. We also observed some small SES-white matter associations and white matter-oral language associations, as well as one white matter-reading association, though these findings need replication given differences between our full sample models and our sensitivity models. As the largest and most diverse study to evaluate SES-brain-reading relations and the only study to test for indirect effects of brain

[5] Note that this total effect is not direct and not better specified by any specific indirect effects (i.e., via vocabulary or PA) in the model and is thus uninterpretable. As such, we do not mention this finding further.

on the association between SES and reading, this study makes an important contribution to the literature. Moreover, differences between our findings and those of other studies raise questions about how factors such as age, sample size and sample diversity may influence white matter associations.

CRediT authorship contribution statement

Perdue Meaghan V.: Writing – original draft, Conceptualization. **Branum-Martin Lee:** Writing – original draft, Supervision. **Landi Nicole:** Writing – original draft, Supervision, Funding acquisition, Conceptualization. **Villa Martina:** Writing – original draft, Visualization, Formal analysis, Data curation, Conceptualization. **Koirala Nabin:** Writing – original draft, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.dcn.2025.101561.

Data availability

open access data was used. Instructions on how to access the unprocessed data is provided.

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