Increased Body Mass Index Is Associated With a Global and Distributed Decrease in White Matter Microstructural Integrity

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Objective: Obesity and decreased physical health are linked to deficits in several cognitive functions. The broad range of cognitive problems linked to obesity suggests a global mechanism that may interfere with multiple neural systems. We examined how variation in body mass index (BMI) is associated with the microstructural integrity of fiber connections in the human brain.

Methods: White matter structure was measured using diffusion tensor imaging in 28 participants (mean age = 30 years) with BMI scores ranging from normal weight to obese (19.5–45.7 kg/m²) based on standard BMI criteria.

Results: Using a whole-brain voxelwise analysis, we found that, across participants, the fractional anisotropy of white matter voxels parametrically decreased with increasing BMI (63% of white matter voxels). Midbrain and brainstem tracts were among the pathways most strongly associated with obesity (r = −0.18 to −0.33, df = 27, all p values < .05). We also observed a weaker overall diffusion signal in individuals with higher BMI than controls with normal weight (r = −0.14 to −0.71, df = 27, for 67% of fiber pathways tested, all p values < .05). After controlling for this decrease in general diffusivity, we found that decreases in fractional anisotropy stemmed from both a decrease in axial diffusivity (p < .05) and an increase in radial diffusivity (p < .05).

Conclusions: Our results show that increased BMI is globally associated with a reduction in white matter integrity throughout the brain, elucidating a potential mechanism by which changes in physical health may influence cognitive health.

Key words: DTI, white matter, fractional anisotropy, body mass index, obesity.

INTRODUCTION

More than a third of the US population is obese (1), and although this decrease in general physical health is usually not considered when assessing cognitive functions, a growing body of evidence suggests that increased obesity is associated with a variety of cognitive impairments. For example, obese individuals exhibit decreased inhibitory control (2–4), working memory (5), and executive control (6) as compared with otherwise healthy individuals. This reduction in cognitive abilities seems to be at least partially linked to cardiovascular health because improving physical health with aerobic exercise improves performance in a variety of cognitive domains such as inhibitory control, spatial memory, and task switching (7). Even in otherwise healthy adults, increased body mass index (BMI), a common quantification of general physical health, is associated with poorer performance on executive function tasks such as the Trail-Making Test and Stroop task (8).

This emerging evidence associating increased BMI with impairments in a variety of cognitive domains suggests a global mechanism by which physical health is related to altered neural functioning. However, most brain imaging studies examining the link between BMI and structural (e.g., gray matter volume) or functional (e.g., task-evoked responses) brain outcomes have focused on isolated cortical areas (9–18). One candidate mechanism by which increased BMI may be associated with neural processing is through the white matter that connects multiple brain regions. In this way, the local changes in the functional activity of cortical areas may be caused by fundamental changes in the axons that connect these regions. Indeed, it has recently been shown that increased BMI is associated with decreased white matter integrity in isolated sections of the corpus callosum and fornix fibers (16,19), with the former pathway being the principal interhemispheric connection for most major cortical areas.

The present study explores how increased BMI is associated with variation in the microstructure of white matter throughout the brain. Diffusion tensor imaging (DTI) was used to characterize the structure of white matter in a group of neurologically healthy individuals across the BMI spectrum. Using a whole-brain voxelwise regression approach, we set out to characterize how variation in BMI relates to the underlying fiber architecture across a distributed range of neural pathways.

MATERIALS AND METHODS

Participants

Neurologically healthy adults (N = 28; 17 females; mean age = 30 years; age range, 18–69 years) were recruited from the local Pittsburgh area. All participants were screened for contraindications to magnetic resonance imaging (MRI) and reported having no neurological conditions including prior head surgery, tumors, stroke, or disease (e.g., Parkinson disease, multiple sclerosis). Immediately before scanning, each participant’s BMI was determined by taking their height (H, in inches) and weight (W, in pounds) using a calibrated scale at the imaging facility and performing the following calculation:

\[
BMI = \frac{W}{H^2}.
\]  

(Eq.1)

A BMI value between 18.5 and 24.9 kg/m² indicates normal weight, between 25 and 29.9 kg/m² indicates overweight, and higher than 30 kg/m² indicates obesity.
BMI INFLUENCES ON WHITE MATTER

indicates obesity. These categories are used only for reference to standard criteria for obesity because BMI was used as a continuous variable in all data analyses reported here.

All testing was approved by the local institutional review board at the University of Pittsburgh. Written informed consent was obtained from all participants before experimentation.

Imaging Acquisition and Processing

Participants were scanned using a Siemens Allegra 3T MRI (Siemens Inc) located at the Brain Imaging Research Center at the University of Pittsburgh. White matter imaging was performed using a 50-direction DTI sequence (2.5-mm isotropic voxels; 40 slices; repetition time, 5500 milliseconds; echo time, 98 milliseconds; b = 1000 s/mm²). Each image is sensitive to the motion of underlying water molecules in a particular direction along a three-dimensional (3D) sphere. These are then used to estimate the structure of underlying water diffusion (see the next section). We also collected five b₀ images that measure nondirectional water diffusion nested in the series to estimate head motion throughout the scan. This was followed by a structural T₁ sequence (Magnetization Prepared Rapid Acquisition with Gradient Echo acquisition; 1-mm isotropic voxels; 256 slices; repetition time, 1400 milliseconds; echo time, 25 milliseconds) for anatomic comparisons.

All image data were reconstructed from k-space using in-house software and saved into the NIFTI image format (http://nifti.nimh.nih.gov/). It is well known that artifacts from eddy current (electric currents generated within the magnetic field due to parameters in the image acquisition process) and head motion can influence the quality of data on an individual participant basis (20). For both cases, rather than run correction algorithms, which can introduce unnecessary noise into the signal, we set up exclusion criteria for individuals who either presented with strong eddy-current artifacts (expressed as a white ring around the edge of the image and time-varying distortion across images) or head motion. A blind and independent observer, trained to identify eddy-current and fat signal artifacts, visually inspected each participant’s data. No eddy-current artifacts were present; however, this is not surprising given the speed of the gradients in the 3T Allegra scanner and the relatively low b-value used. Two participants (one with normal weight and the other who is overweight) containedDepartment of Psychology, Simon Fraser University, Burnaby, British Columbia, Canada, University of British Columbia, Vancouver, British Columbia, Canada, and University of British Columbia, Vancouver, British Columbia, Canada. 16 nonlinear iterations, 1-mm³ FA Montreal Neurological Institute template; FMRIB58_FA_1mm.nii) based on each participant’s FA map. A second alignment step was then performed using an affine linear registration method to manually adjust each participant’s normalized FA map to the group mean FA map. For this, all maps were thresholded at an FA of more than 0.2. This second registration step has been found to minimize cross-participant variance because of the suboptimal nature of the normalization process for diffusion imaging data (21). We then applied this registration to other statistical maps (i.e., λ₁, λ₂, λ₃, ADC) to put all images into the same 3D space for group-level analyses. No image scaling was performed to preserve the total amount of signal in the normalized images because our pilot analysis found that this scaling parameter positively correlated with BMI and thus inflated any BMI-related effects observed in the underlying images. All normalized images were then smoothed with a 3D gaussian kernel (full width at half maximum, 4 mm) before the data analysis procedures described in the next section.

Data Analysis

We first set out to determine how FA varies as a function of BMI. For this, we identified all white matter voxels in the brain by thresholding the mean FA map to a value of more than 0.2. At each voxel within this mask, we performed an iterative sample-with-replacement permutation test (22). We chose to use this “bootstrapping” approach, instead of traditional asymptotic methods, to
maximize our analytical sensitivity given the relatively small sample size. First, the voxel FA values were z-scored across participants. Next, we used an ordinary least squares regression model to remove any effects of age or sex. The residual FA values from this regression were then correlated against the residual BMI values. To test for a significant correlation, we repeated this process 500 times with the BMI and z-scored FA values randomly reassigned across participants. The gray dashed line distribution in Figure 2A shows the average bootstrap-generated chance distribution across all white matter voxels. A bias-corrected and accelerated bootstrap test was used to estimate statistical significance for each voxel (23).

After the bootstrap correlation test, we identified clusters of voxels with significant correlations between FA and BMI. For this analysis, we first applied a threshold for all uncorrected significant voxels \((r_s < -0.33, p < 0.025)\). Clusters of connected voxels within these maps were then automatically identified using edge-based connectivity criteria (24) in SPM8. Clusters with less than 20 connected voxels were discarded from subsequent analysis (i.e., \(k = 20\)). Within each remaining cluster, we identified significant voxels by adjusting the statistical threshold to account for multiple comparisons using a family-wise error correction (false discovery rate of 0.05 (25)). Voxels that survived this threshold are shown in Figures 2B and D.

After whole-brain cluster analysis, we then set out to identify the specific pathways where FA values correlated with BMI and to determine the underlying nature of the FA variations. To do this, we used an established atlas of a priori, anatomically defined white matter regions of interest (ROIs) (26). This atlas identifies 48 segments of core white matter pathways in both hemispheres. To simplify the analysis, we collapsed results across the hemispheres in bilateral pathways. A list of the final 27 ROIs is shown in Table 1.

Our first pass analysis on the atlas-based ROIs used all voxels within each region mask. For this, we determined the percentage of voxels with either a significant negative or positive FA correlation with BMI \((p < 0.025; \text{one tailed, uncorrected})\), the mean correlation value, and the upper and lower bounds of a Bonferroni-corrected 95% confidence interval, determined as follows:

\[
95\% \text{ CI} = \mu \pm \Phi(1 - \alpha/N_{\text{ROIs}}) \frac{\sigma}{\sqrt{N_{\text{voxels}}}}
\]

In Equation 5, \(\mu\) is the mean correlation across voxels, \(\sigma\) is the variance, \(N_{\text{ROIs}}\) is the number of ROIs in the set (i.e., 27), \(N_{\text{voxels}}\) is the number of voxels within the ROI mask, and \(\alpha = 0.05\). Within each selected ROI mask, we determined the mean FA, ADC, \(\lambda_0\), and \(\lambda_\perp\) for all suprathreshold voxels and all participants. The correlation between FA and ADC was first estimated with a Spearman correlation coefficient. Next, the relationship between FA and the two component diffusion parameters \((\lambda_0\) and \(\lambda_\perp\)) was estimated using ordinary least squares regression model after controlling for age, sex, and ADC. In both cases, the adjusted 95% confidence interval of the correlation was determined as shown in Equation 5, with \(\mu = r_s\), \(\sigma\) estimated from the bootstrap distribution, and \(N_{\text{ROIs}} = 12\). These results are presented in Table 2.

**RESULTS**

BMI scores in our participant sample ranged from 19.6 to 45.7 kg/m\(^2\), with a mean (standard deviation) of 26.8 (6.5) kg/m\(^2\) (median = 24.3 kg/m\(^2\)). Thus, our sample reflected a representative range of body sizes, covering the span of normal weight,
TABLE 1. Spearman Correlations Between Body Mass Index and Fractional Anisotropy in 27 A Priori Regions of Interest From a White Matter Atlas

<table>
<thead>
<tr>
<th>Region of Interest</th>
<th>Total No. Voxels</th>
<th>Negatively Correlated Voxels, %</th>
<th>Positively Correlated Voxels, %</th>
<th>Total Significant Voxels, %</th>
<th>Mean $r_s$</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pontine crossing tract</td>
<td>183</td>
<td>32.2</td>
<td>1.1</td>
<td>33.3</td>
<td>−0.33</td>
<td>−0.35 to −0.31</td>
</tr>
<tr>
<td>Corpus callosum (genu)</td>
<td>1131</td>
<td>2.2</td>
<td>0.3</td>
<td>2.5</td>
<td>−0.07</td>
<td>−0.09 to −0.06</td>
</tr>
<tr>
<td>Corpus callosum (body)</td>
<td>1727</td>
<td>5.1</td>
<td>0.0</td>
<td>5.1</td>
<td>−0.12</td>
<td>−0.13 to −0.11</td>
</tr>
<tr>
<td>Corpus callosum (splenium)</td>
<td>1543</td>
<td>1.9</td>
<td>5.8</td>
<td>7.6</td>
<td>0.00</td>
<td>−0.02 to 0.01</td>
</tr>
<tr>
<td>Fornix (main)</td>
<td>81</td>
<td>4.9</td>
<td>0.0</td>
<td>4.9</td>
<td>−0.22</td>
<td>−0.25 to −0.18</td>
</tr>
<tr>
<td>Fornix (striatal terminalis)</td>
<td>284</td>
<td>1.1</td>
<td>2.1</td>
<td>3.2</td>
<td>−0.10</td>
<td>−0.13 to −0.08</td>
</tr>
<tr>
<td>Corticospinal</td>
<td>339</td>
<td>37.2</td>
<td>19.8</td>
<td>56.9</td>
<td>−0.28</td>
<td>−0.31 to −0.25</td>
</tr>
<tr>
<td>Medial lemniscus</td>
<td>169</td>
<td>45.6</td>
<td>19.5</td>
<td>65.1</td>
<td>−0.31</td>
<td>−0.35 to −0.27</td>
</tr>
<tr>
<td>Inferior cerebellar peduncle</td>
<td>208</td>
<td>16.3</td>
<td>43.3</td>
<td>59.6</td>
<td>−0.18</td>
<td>−0.22 to −0.14</td>
</tr>
<tr>
<td>Middle cerebellar peduncle</td>
<td>1898</td>
<td>26.0</td>
<td>46.0</td>
<td>72.0</td>
<td>−0.18</td>
<td>−0.19 to −0.16</td>
</tr>
<tr>
<td>Superior cerebellar peduncle</td>
<td>244</td>
<td>12.3</td>
<td>9.0</td>
<td>21.3</td>
<td>−0.12</td>
<td>−0.17 to −0.07</td>
</tr>
<tr>
<td>Cerebral peduncle</td>
<td>531</td>
<td>17.9</td>
<td>1.7</td>
<td>19.6</td>
<td>−0.14</td>
<td>−0.18 to −0.11</td>
</tr>
<tr>
<td>Internal capsule (anterior limb)</td>
<td>799</td>
<td>7.9</td>
<td>0.0</td>
<td>7.9</td>
<td>−0.14</td>
<td>−0.15 to −0.12</td>
</tr>
<tr>
<td>Internal capsule (posterior limb)</td>
<td>978</td>
<td>4.8</td>
<td>0.0</td>
<td>4.8</td>
<td>−0.16</td>
<td>−0.18 to −0.15</td>
</tr>
<tr>
<td>Internal capsule (retrolenticular)</td>
<td>627</td>
<td>1.0</td>
<td>0.2</td>
<td>1.1</td>
<td>−0.06</td>
<td>−0.08 to −0.04</td>
</tr>
<tr>
<td>External capsule</td>
<td>1421</td>
<td>1.9</td>
<td>0.5</td>
<td>2.4</td>
<td>−0.08</td>
<td>−0.09 to −0.07</td>
</tr>
<tr>
<td>Corona radiata (anterior)</td>
<td>1721</td>
<td>2.7</td>
<td>0.0</td>
<td>2.7</td>
<td>−0.10</td>
<td>−0.11 to −0.08</td>
</tr>
<tr>
<td>Corona radiata (superior)</td>
<td>1844</td>
<td>7.7</td>
<td>0.1</td>
<td>7.8</td>
<td>−0.14</td>
<td>−0.15 to −0.13</td>
</tr>
<tr>
<td>Corona radiata (posterior)</td>
<td>898</td>
<td>2.9</td>
<td>0.0</td>
<td>2.9</td>
<td>−0.06</td>
<td>−0.07 to −0.04</td>
</tr>
<tr>
<td>Thalamic radiation (posterior)</td>
<td>965</td>
<td>3.8</td>
<td>0.0</td>
<td>3.8</td>
<td>−0.10</td>
<td>−0.11 to −0.08</td>
</tr>
<tr>
<td>Sagittal stratum</td>
<td>574</td>
<td>0.0</td>
<td>1.0</td>
<td>1.0</td>
<td>0.02</td>
<td>0.00 to 0.04</td>
</tr>
<tr>
<td>Cingulum (cingulate gyrus)</td>
<td>631</td>
<td>0.2</td>
<td>1.3</td>
<td>1.4</td>
<td>−0.02</td>
<td>−0.04 to 0.00</td>
</tr>
<tr>
<td>Cingulum (hippocampus)</td>
<td>284</td>
<td>12.3</td>
<td>8.5</td>
<td>20.8</td>
<td>−0.13</td>
<td>−0.16 to −0.09</td>
</tr>
<tr>
<td>Superior longitudinal fasciculus</td>
<td>1640</td>
<td>4.4</td>
<td>0.2</td>
<td>4.6</td>
<td>−0.09</td>
<td>−0.10 to −0.08</td>
</tr>
<tr>
<td>Superior fronto-occipital fasciculus</td>
<td>114</td>
<td>19.3</td>
<td>0.0</td>
<td>19.3</td>
<td>−0.27</td>
<td>−0.31 to −0.24</td>
</tr>
<tr>
<td>Uncinate fasciculus</td>
<td>96</td>
<td>0.0</td>
<td>1.0</td>
<td>1.0</td>
<td>0.07</td>
<td>0.05 to 0.10</td>
</tr>
<tr>
<td>Tapetum</td>
<td>149</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.03</td>
<td>0.00 to 0.06</td>
</tr>
</tbody>
</table>

FA = fractional anisotropy; ADC = apparent diffusion coefficient; AD = axial diffusivity; RD = radial diffusivity.

Means and 95% confidence intervals are displayed for Spearman correlations ($r_s$) between FA and ADC. Ordinary least squares regression, controlling for ADC, was used to estimate the relationship between FA and both RD and AD in separate regression models. Parameter estimates ($\beta$) and 95% confidence intervals are reported.

TABLE 2. Water Diffusion Component Relationships Estimated Using a Bootstrapped Regression Method for the Regions of Interest in Table 1 With More Than 5% of Voxels Having a Significant FA-BMI Relationship

<table>
<thead>
<tr>
<th>Region of Interest</th>
<th>No. Voxels</th>
<th>$r_s$</th>
<th>95% Confidence Interval</th>
<th>$\beta$</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pontine crossing tract</td>
<td>59</td>
<td>−0.14</td>
<td>−0.23 to −0.05</td>
<td>517</td>
<td>305 to 729</td>
</tr>
<tr>
<td>Corpus callosum (body)</td>
<td>88</td>
<td>0.01</td>
<td>−0.04 to 0.07</td>
<td>1351</td>
<td>103 to 2598</td>
</tr>
<tr>
<td>Corticospinal</td>
<td>126</td>
<td>−0.18</td>
<td>−0.24 to −0.12</td>
<td>653</td>
<td>607 to 698</td>
</tr>
<tr>
<td>Medial lemniscus</td>
<td>77</td>
<td>−0.34</td>
<td>−0.43 to −0.26</td>
<td>460</td>
<td>184 to 736</td>
</tr>
<tr>
<td>Inferior cerebellar peduncle</td>
<td>34</td>
<td>−0.38</td>
<td>−0.50 to −0.26</td>
<td>717</td>
<td>566 to 868</td>
</tr>
<tr>
<td>Middle cerebellar peduncle</td>
<td>494</td>
<td>−0.45</td>
<td>−0.49 to −0.42</td>
<td>459</td>
<td>423 to 495</td>
</tr>
<tr>
<td>Superior cerebellar peduncle</td>
<td>30</td>
<td>−0.32</td>
<td>−0.46 to −0.18</td>
<td>928</td>
<td>12 to 1844</td>
</tr>
<tr>
<td>Cerebral peduncle</td>
<td>95</td>
<td>−0.72</td>
<td>−0.80 to −0.63</td>
<td>402</td>
<td>246 to 558</td>
</tr>
<tr>
<td>Internal capsule (anterior limb)</td>
<td>63</td>
<td>0.00</td>
<td>−0.10 to 0.10</td>
<td>1857</td>
<td>−505 to 4218</td>
</tr>
<tr>
<td>Corona radiata (superior)</td>
<td>142</td>
<td>−0.11</td>
<td>−0.16 to −0.06</td>
<td>1537</td>
<td>547 to 2528</td>
</tr>
<tr>
<td>Cingulum (hippocampus)</td>
<td>35</td>
<td>0.08</td>
<td>−0.22 to 0.05</td>
<td>801</td>
<td>157 to 1444</td>
</tr>
<tr>
<td>Superior fronto-occipital fasciculus</td>
<td>22</td>
<td>−0.25</td>
<td>−0.45 to −0.06</td>
<td>2039</td>
<td>−2082 to 6159</td>
</tr>
</tbody>
</table>

FA = fractional anisotropy; ADC = apparent diffusion coefficient; AD = axial diffusivity; RD = radial diffusivity.

Means and 95% confidence intervals are displayed for Spearman correlations ($r_s$) between FA and ADC. Ordinary least squares regression, controlling for ADC, was used to estimate the relationship between FA and both RD and AD in separate regression models. Parameter estimates ($\beta$) and 95% confidence intervals are reported.
overweight, and obese. To ensure that our sample was large enough to make valid statistical comparisons, we performed a power analysis based on the effect sizes reported in a recent study (see Table 1 in Mueller et al. (19)). Our analysis, assuming a bivariate normal distribution, showed that a sample of 19 to 27 participants was sufficient to reliably reject a null hypothesis with an \( \alpha \) of 0.05. In this sample, we did not detect a significant correlation between age and BMI (\( r_s = 0.24, p = .12 \)), and there was no significant difference in BMI scores between men and women (independent sample \( t < 1, df = 26, p = .52 \)).

A voxelwise nonparametric correlation analysis between FA and BMI, after controlling for age and sex, found that FA was negatively correlated with BMI across most (63.3%) white matter voxels in the brain (Fig. 2A). There was a clear distribution shift from the expectations of random chance (dashed black line in Fig. 2A). Correlations ranged from -0.73 to 0.74, with a mean (standard deviation) of -0.05 (0.18) and a median of -0.06.

Of the isolated clusters of voxels for which the correlations were statistically significant (\( p < .025 \); blue and red bars in Fig. 2A), most were negative (6.5% significant negative correlations versus 1.6% positive). Although at first, this number may seem small, it is important to put it into context. The number of significant voxels negatively correlated with BMI is well above the 2.5% expectations of chance (based on a one-tailed \( p = .025 \)). Given the number of voxels tested (80,777), this means that 5250 voxels passed this stringent threshold, spanning 1050 mm\(^2\) of tissue.

After controlling for multiple comparisons, we identified several pathways with a significant negative relationship between FA and BMI (Fig. 2B). Subcortically, the middle and superior cerebellar peduncles showed strong BMI effects. Clusters were also present bilaterally in the medial lemniscus regions of the midbrain, in the infundibulum that connects the hypothalamus to the pituitary, along portions of the anterior limb of the internal capsule, and in perithalamic white matter. We found that several pathways containing corticocortical or cortical-subcortical projections were also negatively correlated with BMI, including regions of the cingulum, the semioval (i.e., corona radiata), and perihippocampal white matter in the temporal lobe.

The clusters shown in Figure 2B are labeled based on an approximate visual identification of gross anatomic landmarks. Based on an atlas of a priori defined anatomic ROIs (26), we found a consistent trend for stronger negative associations between BMI and FA (Table 1). In most cases, there were many more voxels with significant (\( p < .025 \), one tailed) negative correlations than positive. The percentage of voxels with significant negative correlations was well above chance expectations in 12 pathways (shown in Table 2). However, in all but four tracts, the mean correlation across voxels was negative, and the adjusted 95% confidence interval of the correlation value did not include 0. This suggests that, even in pathways with relatively few suprathreshold voxels, the trend across the entire white matter tract was for a consistently negative association with BMI.

So far, our analysis has demonstrated a consistent negative relationship between BMI and FA across white matter pathways in the brain. As mentioned previously, FA can decrease from either a decrease in \( \lambda_3 \) or increase in \( \lambda_1 \). Of course, these are not mutually exclusive possibilities, meaning that FA can also vary because of altered diffusivity in both planes. However, we first need to ascertain whether BMI is correlated with the magnitude of the diffusion signal itself (i.e., the energy of diffusion in the underlying voxels). To determine this, we used a similar whole-brain correlation analysis to look at how ADC correlated with changes in BMI. Similar to FA, we found that, in white matter voxels, the ADC was generally negatively correlated with BMI (Fig. 2C).

At first glance, this global correlation of BMI with overall energy in the diffusion signal may also seem to explain the relationship with FA. However, FA is a measure of shape, not overall diffusion magnitude, and changes in overall diffusion can occur symmetrically to all components that go into the FA calculation, resulting in little change to the actual FA value (Eq. 2). To get a quantitative estimate of the relationship between FA and ADC, we identified the voxels with significant negative BMI and FA correlations within the 12 fiber tracts with the strongest BMI effects. In 8 of 12 ROIs tested, we found a significant negative relationship between FA and ADC (Table 2). This suggests that the variation in the energy of the diffusion signal is not expressed symmetrically for all components of the FA equation.

To determine how much of the variance in the original FA and BMI correlation is explained by ADC effects, we used a nested regression analysis to measure how the FA-BMI relationship changes after accounting for ADC. For this analysis, we took the average FA values from voxels in the 12 ROIs shown in Table 2, which were negatively correlated with BMI (\( p < .025 \), one tailed). In one regression model, we correlated the influence of BMI, age, and sex on the average FA. We then compared coefficients from this to those from a model that also included ADC as a covariate. As expected, the regression coefficients for BMI on FA were negative in the first regression model without controlling for ADC across the 12 ROIs tested (-0.005 ± 0.0021 [standard error]). Including the ADC term in the second model reduced the magnitude of this BMI coefficient on an average of 8.06% (±12.18%) across all 12 ROIs to a value of -0.0036 (±0.0014). For comparison, we repeated the second controlled regression model except with the ADC term replaced with a random noise parameter with the same mean and variance as the ADC values at each ROI. With this random regressor, we observed a slight but not substantial drop in the BMI coefficient magnitude (-0.0048 ± 0.0021). Thus, accounting for ADC generally reduced the magnitude of the relationship between BMI and FA by 8%.

Because overall diffusivity decreased with increased BMI and this also has an influence on the overall FA-BMI relationship, we included ADC as a covariate in our analysis to determine whether our BMI association with FA reflected a change in \( \lambda_3 \) or \( \lambda_1 \) or both. Table 2 shows the results of this analysis for affected voxels in the 12 fiber pathways with the strongest negative BMI-FA effects. After controlling for ADC, we found that diffusivity in the axial direction was positively...
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correlated with FA in all but two of the regions. In addition, we found that FA negatively correlated with diffusivity in the radial plane for the same 10 pathways. The only two fiber tracts that did not show this pattern were the anterior limb of the internal capsule and the superior fronto-occipital fasciculus. This suggests that, in most pathways, the BMI-related reduction in FA is associated with both a decrease in \( \lambda_0 \) and an increase in \( \lambda_\perp \). We discuss this in more detail in the next section.

Although we were more than four times more likely to see a negative relationship between BMI and FA than a positive correlation, there were still several clusters with strong positive relationships (Fig. 2D; see also red section of the distribution in Fig. 2A). These clusters were also located primarily in subcortical and brainstem regions, particularly the middle cerebellar peduncle and the fiber pathways near the colliculus. In most cases, fiber tracts with a large number of significant positive correlations also had a substantial, if not greater, number of negatively correlated voxels (Table 1). Of the 27 ROIs tested, only the splenium of the corpus callosum did not share this collinear pattern. Therefore, in most regions where positive associations between BMI and FA were observed, this relationship might be explained by the inefficiency of the microstructural integrity may have a global, whole-brain relationship that is particularly strong in brainstem sensory and motor pathways. Because these effects seem to originate from altered diffusivity in the axial and radial planes, there may be multiple mechanisms by which increased BMI is associated with white matter.

These findings build on a growing body of literature on brain differences associated with increased BMI. Stanek and colleagues (16) recently used an ROI-based approach to show how the FA of voxels in the corpus callosum and fornix decreased with higher BMI. This was recently validated by a similar analysis on tract-based white matter segments, also focusing primarily on the corpus callosum, by Mueller and colleagues (19). In addition to the BMI-FA relationship, Mueller and colleagues (19) also found a specific relationship between decreased FA and \( \lambda_0 \), along with an increase in \( \lambda_\perp \) in women but not in men. Additional support of our findings comes from Yau and colleagues (29), who recently reported decreased integrity of cerebral white matter in adolescents with Type 2 diabetes, an obesity-associated disease. In fact, obesity combined with Type 2 diabetes is associated with elevated rates of atrophy of multiple brain areas (10,11,15–17). More recently, adults having Type 2 diabetes have been shown to have less overall gray matter than healthy controls (30). Although we did not test for insulin resistance in the present study, it may be a possible mechanism for the changes in white matter integrity, which were observed.

Our work extends on these previous findings in several ways. First, we show how increased BMI is associated with a global decrease in white matter integrity throughout the brain. If BMI only related to isolated clusters or specific pathways, then the global distribution of correlations would be slightly skewed or contain heavy tails but with a mean overlapping the null distribution. Instead, we found that the distribution of correlations had a similar shape as what would be expected by chance (i.e., normally distributed), based on bootstrapping tests, but shifted in the negative direction. This global expression may also explain the heterogeneity in the location of significant negative clusters between research samples (compare our results to those reported by Stanek et al. (16) and Mueller et al. (19)). If the mechanisms by which obesity influences axonal structure were nonspecific, then different samples of participants would exhibit different patterns of significant clusters. Thus, adopting a whole-brain distribution approach such as that shown in Figures 2A and C may be the best way to compare findings across studies.

Second, we found a consistent association between BMI and FA in subcortical brainstem pathways that were not reported in these previous studies. The location and bilateral expression of many of these clusters validates that these are not simply the expression of random noise. Many of these pathways are linked to sensory and motor functions. For example, we found that both input (middle and inferior peduncle) and output (superior peduncle) pathways to the cerebellum correlate with BMI. If replicated, these findings would suggest that obese individuals might express errors in control and coordination of motor behaviors consistent with cerebellar dysfunction. We also found that the integrity of a major sensory input pathway to the primary somatosensory cortex, the medial lemniscus, was negatively associated with increasing BMI. This suggests that participants with high BMI may experience deficits in fine tactile sensation, including proprioception or vibrotactile experience (see Willis (31) for review of this system). Alternatively, these effects may simply reflect the consequences of an increased sedentary life-style in obese individuals (32) rather than the result of changes to physiological systems.

We also showed that increased BMI was associated with the energy in the overall diffusion signal itself. Indeed, approximately 8% of the variance in the BMI-FA relationship could be explained by a reduction in the energy of the diffusion signal. Variations in ADC could result from differences in body temperature or physiological noise in individuals with higher BMI or might reflect true changes to underlying axonal structure.

We discuss this in more detail in the next section.
ADC is, in fact, often used as a measure of white matter integrity itself, and it is highly correlated with mean diffusivity, calculated as the mean of the three eigenvectors used in the FA calculation (see Materials and Methods). Conceptually, the association between BMI and both FA and ADC suggests a multifaceted relationship where both the shape and magnitude of axonal integrity might decrease with increased obesity. Future studies using high angular resolution imaging approaches, combined with orientation diffusion function reconstructions, such as high angular resolution imaging and diffusion spectrum imaging (see Hagmann et al. (28) for review), might be able to dissociate these two effects on underlying white matter structure. More importantly, however, this finding suggests that any interpretation of DTI results in relation to obesity, which do not include a control for changes in the diffusion signal, may be biased or provide incomplete characterizations of neuroanatomic changes.

Our finding that BMI-linked variation in FA was positively correlated with \( \lambda_1 \) and negatively correlated with \( \lambda_2 \) is generally consistent with recent findings using a larger sample of participants (19). Although in this earlier study, only female participants demonstrated correlations with both changes in axial and radial diffusions, whereas obese male participants only exhibited changes in \( \lambda_2 \). It is likely that our limited sample size precludes our ability to disentangle sex-related differences in these systems. Neuroanatomically, these different signals provide some indications as to the structure of the underlying white matter itself. Animal models of white matter degeneration have shown that decreased \( \lambda_1 \) correlates with atrophy of axonal fibers (33–34), whereas increased \( \lambda_2 \) corresponds to demyelination (35–36). This bimodal change in the shape of the diffusion signal suggests that there are likely multiple mechanisms contributing to the relationship between BMI and FA. However, this relationship between FA, \( \lambda_1 \), and \( \lambda_2 \) only holds in voxels containing uncrossed fiber tracts (e.g., corpus callosum, internal capsule (37)). The limited resolution of the diffusion tensor model at resolving fiber crossings means that these presumed relationships break down in regions with more complex fiber patterns (e.g., corona radiata, superior longitudinal fasciculus). Future work should take this into account when exploring the nature of white matter variations associated with increased obesity.

Obesity itself is associated with a range of general physiological changes, including increased inflammation; changes in glucose and insulin systems, which can result in Type 2 diabetes; and increases in cholesterol and hypertension (38–39). Therefore, it is possible that several of these physiological comorbidities with obesity may also mediate the association between BMI and white matter. For example, a small functional MRI study showed that obesity was associated with reductions in brain activity during the performance of a demanding working memory task and that the strongest predictor of reduced activation was not higher BMI but lower insulin sensitivity (18). In addition, inflammatory pathways have been implicated in white matter atrophy in both humans (40) and animal models (41) and also increase with obesity. Neuropsychological studies have suggested that some cognitive domains supported by these same brain areas are compromised in obesity (e.g., planning and mental flexibility, problem solving, memory, psychomotor speed (42–45)). Unfortunately, because those studies have inconsistently and incompletely measured both cognitive outcomes and physiological predictors, and often use small, nonrepresentative samples, it is not possible to draw strong conclusions about physiological-cognitive-neurological relationships. Only further studies, on larger sample sizes with physiological markers, can begin to address these mechanistic questions.

Of course, cardiovascular changes could also play a critical role in mediating the relationship between obesity and white matter. A recent study found that increased mean arterial blood pressure was associated with a reduction in white matter integrity, assessed using DTI, in the corpus callosum in a sample of African American adults (38). Cortically, increased blood pressure was also associated with a reduction in gray matter thickness in frontal, parietal, and temporal association cortices (46). These findings suggest that increased blood pressure might mediate obesity-related effects on white matter and neurocognitive performance. However, it should be pointed out that the previous studies associating blood pressure with brain morphology failed to include measures of body weight or obesity, so this relationship has not yet been directly tested. In addition, a more recent study found that variation in blood pressure did not significantly mediate the relationship between white matter changes and cognitive performance in a sample of healthy older adults (39). However, neuroanatomic measures of hypertension (reflected as white matter signal abnormalities) did mediate the relationship between white matter integrity and cognition. Despite this ambiguity on the role of cardiovascular integrity in neurocognitive relationships, these results suggest that future studies should include measures of cardiovascular integrity when exploring the mediating pathways linking obesity to neural morphology metrics.

One potential limitation of the present study is the small sample size used; however, we believe that this is not a significant limitation for several reasons. First, in statistical theory, sample size and effect size interact when determining the power of any statistical inference. In a previous study, Mueller and colleagues (19) reported correlations between BMI and FA in the corpus callosum, depending on group and location, which ranged from \(-0.779\) to \(-0.673\) (see Table 1 in Mueller et al. (19)). A power analysis on these effect sizes indicates that a sample size ranging from 19 to 27 participants is sufficient to adequately reject the null hypothesis. Therefore, our sample is not underpowered. Second, if the sample size was causing low power in our analysis, then the likelihood of a false positive would be equal to that of a false negative. Our distribution analysis clearly shows a symmetrical distribution but with a greater likelihood of negative correlations than positive (Fig. 2A). This suggests that the within-sample noise was small enough to allow for any underlying effects to be visible. Third, as mentioned previously, our findings are similar to recent reports in restricted ROIs (16,19), further validating our observed effects. Finally, the use of both nonparametric and
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permutation statistics reduces the influence of outliers on the final outcome. The conservative nature of these tests reduces the possibility of Type I errors. Nonetheless, studies with larger sample sizes are necessary before making conclusive arguments about the impact of BMI on brain health.

Another major limitation is that we cannot determine whether the white matter correlations with BMI are associated with body weight changes or due to secondary disorders linked to obesity. For example, as mentioned previously, obesity is associated with increased prevalence of Type 2 diabetes (see Kahn et al. (47)). It is possible that increased insulin resistance in our overweight and obese participants may be the fundamental molecular mechanism that mediates changes in white matter structure. Unfortunately, this experiment represents a pilot study that was intended to define the scope of future research. Therefore, ancillary measures of obesity such as waist circumference or the hip-to-waist ratio and measures underlying physiological systems such as inflammatory markers, cholesterol levels, or insulin and glucose levels were not collected in this sample. Future studies should collect more information of both physical health and physiological systems to isolate the root mechanisms underlying the relationship between obesity and white matter.

However, BMI can serve as a useful “umbrella” measure that encompasses this broader range of underlying mechanisms for both scientific and public health purposes. If a direct relationship between BMI and white matter structure is confirmed, then intervention studies should be conducted to determine whether reducing BMI within an individual improves the integrity of white matter. Recently, exercise interventions have been shown to attenuate age-related declines in both cognitive function (48) and brain volume (49–51). Perhaps similar interventions would show promise in attenuating the effect of BMI in similar cognitive and neural systems.

So far, we have worked under the presumption that certain underlying systems linked to obesity drive changes in white matter pathways. However, because our analysis is strictly correlational in nature, it does not explicitly preclude other possible explanations for this relationship. One possibility is that an unknown third variable is concurrently driving both changes in white matter and obesity, such as a genetic condition that both decreases white matter and makes individuals more susceptible to obesity. Another possibility is that individual differences in baseline white matter integrity may influence behavioral patterns and, in turn, increase obesity. For example, persons with innately lower white matter integrity, for example in inhibitory control pathways, may be more likely to exhibit hedonic overeating. Given the observations that exercise interventions can preserve other brain morphology measures (50), we believe that this inherent differences hypothesis is highly unlikely. However, it is possible that changes in white matter may subsequently lead to further increased BMI, resulting in a positive-feedback loop between white matter and obesity. Only targeted intervention studies can determine if such cycles occur.

Nonetheless, our findings provide several important contributions to the existing literature. We independently validate the relationship between BMI and white matter integrity reported in two recently published studies (16,19). We also extend these findings by showing that the association of BMI with white matter integrity is a globally distributed phenomenon and not limited to a select group of major white matter pathways such as the corpus callosum. We show that individuals with high BMI have an overall weaker diffusion signal and this accounts for part of the relationship between BMI and FA. Finally, we demonstrate that, after accounting for this signal difference, BMI-related FA changes are linked to changes in both the axial and radial diffusion directions. The degree and scope of BMI-related white matter changes and its distributed influence throughout the brain should be of concern to both clinical and basic science researchers alike.

REFERENCES


