Multimodal population brain imaging in the UK Biobank prospective epidemiological study

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Medical imaging has enormous potential to provide early predictors of disease, yet has long been impeded by the difficulty and expense associated with acquiring datasets prior to symptom onset. UK Biobank aims to tackle this problem by conducting the largest population-level imaging study to date. High quality, consistently acquired imaging data will be collected from 100,000 participants, whose health outcomes will then be tracked over coming decades. Brain imaging in UK Biobank includes six structural, diffusion and functional modalities that, along with genetics, hundreds of lifestyle measures, biological phenotyping and health records, are expected to enable the discovery of imaging markers of a broad range of diseases at their earliest stages, as well as provide unique insight into disease mechanisms. We describe here the UK Biobank brain imaging study, and present results from the brain imaging data in the first open data release, comprising imaging data from around 5,000 participants. Although this covers just 5% of the ultimate imaging cohort, it already yields a rich range of associations between brain imaging and other measures collected by UK Biobank. These results presage a new era in brain imaging, in which complex phenotypic interactions can provide sensitive early markers of disease and aging.

The primary clinical role of brain imaging to date has been in diagnosis and monitoring of disease progression, rather than providing predictive markers of risk that might enable preventative stratification or early therapeutic intervention. The predominant strategy in the search for image-based markers of neurological and psychiatric disease has been to identify patients early in the diagnostic process, with the goal of maximizing statistical power in a small cohort (commonly less than 50, with hundreds of subjects considered a large study). A key factor motivating the use of small cohorts is the expense, time and specialized hardware associated with gathering imaging data. This approach has been effective in providing markers of disease progression, but identifying imaging markers of early disease requires measurements at the pre-symptomatic stage. Image-based measures of brain structure and function may evolve in a complex way throughout the course of aging and progression of neuropathology. Therefore, markers with utility in monitoring disease progression post-diagnostically may not manifest pre-symptomatically, and conversely the most sensitive early predictors of disease may have plateaued by the time existing diagnoses become accurate.

Nevertheless, imaging has demonstrated the ability to stratify subjects long before symptom presentation, when known risk factors can be used to assemble focused cohorts. For example, magnetic resonance imaging (MRI) has demonstrated altered brain activity associated with APOE genotype decades in advance of symptoms associated with Alzheimer's disease[1], and early prediction of Alzheimer's has been demonstrated through combined analysis of structural and diffusion MRI[2]. These studies demonstrate that MRI can achieve sensitivity to tissue changes that precede symptoms, and suggest that the primary obstacle to identifying early imaging markers is in obtaining data in pre-symptomatic cohorts drawn from the general population.

An alternative is to adopt a prospective approach, in which a large cohort of healthy participants are intensively phenotyped (including imaging) and subsequently monitored for long-term health outcomes. While this approach is expensive, it is also efficient by capturing early biomarkers and risk factors for a broad range of diseases. It further becomes possible to discover unexpected interactions between risk factors (such as lifestyle, genetics and early life factors). To date, the largest brain imaging studies have gathered data on a few thousand subjects, often including rich phenotyping[3-9]. While this approach has been effective for identifying associations between imaging and highly prevalent diseases, such cohorts are still too small to produce sufficient incidence of many diseases of interest where participants are recruited without identifying risk factors. Here, we present one of the first large population brain imaging studies designed to address the challenge of recruitment from a large enough population to include a range of , UK Biobank.

UK Biobank is a prospective epidemiological study gathering extensive questionnaires, physical and cognitive measures and biological samples (including genotyping), in a cohort of 500,000 participants[10]. Crucially, participants consent to providing access to their full health records from the UK National Health Service, enabling the study to relate phenotypic measures to long-term health outcomes. The study is particularly powerful due to this combination of number of subjects and wide range of linked data. Participants were 40-69 years of age at baseline recruitment, which aims to balance the goals of characterizing subjects prior to disease onset against the delay required before health outcomes accumulate. As such, the cohort is particularly appropriate for study of neuropathologies associated with aging. All data from UK Biobank are available to researchers world-wide upon application for access, with no preferential access for scientists leading the study. Funding was confirmed in early 2016 for an imaging extension to the existing UK Biobank study that will scan 100,000 subjects from the existing cohort. Imaging includes MRI of the brain, heart and body; very-low-dose x-ray bone and joint scans; and ultrasound of the carotid arteries. Identification of disease risk factors should increase over time with emerging clinical outcomes. For example, within the imaged cohort, 1800 participants are expected to develop Alzheimer's disease by 2022, rising to 6000 by 2027 (diabetes: 8000 rising to 14,000; stroke: 1800 to 4000; Parkinson's: 1200 to 2800)[11].

The dataset will enable many kinds of studies, some of which we now briefly describe (also, in the Discussion, we review a range of analytic approaches that might be brought to bear for such studies). The most obvious is the identification of novel imaging biomarkers of future disease risk. Such biomarkers also could support diagnosis, development of therapeutics, and assessment of interventions. The availability of multi-modal, multi-organ imaging in UK Biobank also creates valuable opportunities to study interactions between organ systems, for example, between baseline cardiovascular health and later development of dementia. The breadth of imaging (organ systems and modalities) makes this dataset particularly valuable for multi-systemic syndromes such as frailty, a broad index of accelerated aging characterized by a general loss of reserves and poor tolerance to stressors, which indicates increased risk for a range of conditions including dementia[12]. A third opportunity offered by Biobank is to suggest hypotheses regarding causal mechanisms of that could then be tested in follow-up interventional studies. This also includes identification of modifiable risk factors, such as the association of obesity with later life cognitive dysfunction[13], and importantly the ability to study complex interactions these risk factors have with other factors e.g., lifestyle, environment and genetics. Finally, as a very large, rich dataset, the UK Biobank will enable validation of associations identified by smaller-scale, focused studies (and evaluation of the extent to which multiple previous separate results from individual imaging modalities may be combined into larger coherent multimodal hypotheses). Moreover, the large, ultimately clinically diverse cohort will enable both replication and extension of studies conducted on selected subject groups.

RESULTS

Design rationale and first imaging center – scanning outcomes, data processing and first data release

The imaging study was designed to achieve the target of 100,000 subjects over 5-6 years at three dedicated, identical imaging centers operating 7 days/week, each scanning 18 subjects/day[14]. This implied tight timing constraints, corresponding to one subject completed every 36 minutes (as discussed in Online Methods). The first imaging center was built to prove feasibility and scanned 9,000 subjects over a two-year ramp-up period.

Two further identical centers will be commissioned during 2016, with the three centers strategically positioned at population hubs: Manchester, Reading and Newcastle.

The goal of capturing imaging phenotypes relevant to the widest possible range of diseases and hypotheses meant that the protocol must deliver data with the broadest predictive power for neuropathology and mental health. The resultant brain imaging protocol (**Supplemental Table 1**) included three structural modalities, T1-weighted, T2-weighted and susceptibility-weighted MRI (referred to here as T1, T2 and swMRI); diffusion MRI (dMRI); and both task and resting-state functional MRI (tfMRI and rfMRI). By utilizing recent advances in MRI acquisition technology[15], we were able to obtain high quality data, for example 2.4mm resolution whole-brain fMRI data with a temporal resolution of 0.7 seconds, and 2mm resolution dMRI data in 100 diffusion-encoding directions (split over 2 b-value shells), in just 7 minutes. This latter enables advanced model fitting of microstructural parameters that would not have been possible under these time constraints with previous generation technology. Following optimization of acquisition protocols, streamlining of participant preparation and minimization of scanner dead time (see Online Methods), UK Biobank was able to incorporate six neuroimaging modalities in just 36 minutes per participant.

Unlike most of the measurements included in the original UK Biobank resource (such as birth weight, alcohol consumed per week and cognitive test scores), raw imaging data is not a directly useful source of information. This is in part because of the need for image processing to remove artefacts and align images to achieve correspondence across modalities (and individuals), but also because most useful image phenotypes are derived through complex calculations combining MRI signals from many voxels and often over multiple images. A fully automated processing pipeline was developed, producing both processed images as well as image-derived phenotypes (IDPs) – thousands of distinct individual measures of brain structure and function. Example IDPs include: the volume of specific brain structures; the strength of connectivity between pairs of brain regions; the estimated dispersion of fibers in a given white matter tract; and brain activity when viewing emotionally negative faces. IDPs are intended to be useful for non-imaging experts; however, understanding of the confounds and pitfalls of imaging is required to draw appropriate conclusions.

We present results from the first data release (biobank.ctsu.ox.ac.uk/crystal/label.cgi?id=100), which includes outputs from the processing pipeline for 5285 subjects scanned in 2014-2015. As determined by the processing pipeline, 98% of participants' datasets resulted in a usable T1-weighted image, which is crucial for deriving usable information from the other modalities. Of these, data for the other brain imaging modalities were suitable for processing in the following percentages of subjects: T2=97%, swMRI=93%, dMRI=95%, tfMRI=92%, rfMRI=95%. All modalities were acquired and usable in 89% of the subjects. Results from this data release are illustrated in **Figs 1-4,** including a group-averaged multimodal atlas available for download and online browsing (www.fmrib.ox.ac.uk/analysis/techrep/ukb). We also present example analyses using the brain imaging data, including voxel-wise analyses of age effects, pair-wise correlations of brain IDPs with other subject measures, and finally a more integrated multivariate analysis that identified dominant population patterns linking brain IDPs to other measured parameters.

Imaging data, atlases and imaging-derived phenotypes

Data from the three structural modalities (T1, T2 and swMRI) are shown in **Fig 1**. These data provide information about different aspects of the brain's tissues, structures and neuropathologies. Data quality at the single-subject level is illustrated in **Fig 1a,b,** where the images have undergone minimal preprocessing (just removal of intensity inhomogeneity and faces/ears blanked for anonymisation). The group-averaged images produced for each modality are high-quality atlases (**Fig 1c-f**), depicting strong tissue contrast and excellent fidelity of non-rigid alignment across subjects; the resulting multimodal population atlas forms part of the initial data release. The T1 modality (**Fig 1a,c**) is the most informative about the basic structure of the brain, including the depiction of the main tissue types (gray and white matter) and gross structure of the brain (main anatomical landmarks). From the T1 data, we derived 25 volumetric IDPs: total tissue volumes (gray, white and ventricular cerebro-spinal fluid), and the volumes of subcortical grey matter structures such as thalamus, caudate, putamen, pallidum, hippocampus and amygdala. The T1 data and T1-derived IDPs provide sensitive markers of atrophy (tissue loss), which can be both global (e.g., thinning of the cortex in aging)[16] and local (e.g., reduction of hippocampal volume in Alzheimer's disease)[17]. The T2 FLAIR (fluid-attenuated inversion recovery) data (**Fig 1b,d**) also depicts basic anatomy, but is valuable primarily for detection of focal neuropathology that appears as white matter hyperintensities. These white matter lesions have been associated with a broad range of neuropathological conditions[18] (e.g., small vessel ischaemic disease), as well as occurring with increasing incidence in aging populations without (or potentially before) manifestation of neurological symptoms. IDPs relating to the volume of these white matter lesions will be included in future data releases. swMRI is a flexible modality that can be processed in multiple ways, each sensitive to different clinically-relevant properties. The first data release includes T2* relaxation time mapping and enhancement of venous vasculature using

susceptibility-weighted image (SWI) filtering[19] (**Fig 1e,f)**. swMRI IDPs in the current data release are the median signal decay times (T2*) in each of 14 major subcortical gray matter structures, for example reflecting increased iron deposition associated with neurodegeneration[20].

Figure 1 Data from the three structural imaging modalities in UK Biobank brain imaging. (**a**) Single-subject T1-weighted structural image with lower neck areas cropped and the face blanked to protect anonymity. Color overlays show automated modeling of several subcortical structures (above) and segmentation of gray matter (below). (**b**) Single-subject T2-weighted FLAIR image, with hyperintense lesions in the white matter indicated (arrows). (**c**) Group-average (n≈4500) T1 atlas; all subjects' data were aligned together (see Online Methods for processing details) and averaged, achieving higher quality alignment, with clear delineation of deep grey nuclei and good agreement of major sulcal folding patterns despite wide variation in these features across subjects. (**d**) Group-average T2 FLAIR atlas. (**e**) Group-average SWI atlas derived from SWI processing of swMRI phase and magnitude images. (**f**) Group-average T2* atlas, also derived from the swMRI data. (**g**) "Manhattan" plot (a layout common in genetic studies) relating all 25 IDPs from the T1 data to 1100 non-brain-imaging variables extracted from the UK Biobank database, with the latter arranged into major variable-type groups along the x axis. For each of these 1100 variables, the strength of the cross-subject univariate correlation with each of the IDPs is plotted vertically, in units of $-\log_{10}(P)$. The dotted horizontal lines indicate thresholds corresponding to multiple comparison correction using false discovery rate (lower line) and Bonferroni correction (upper line) across the 2.8 million tests involving all modalities' IDPs. Effects such as age, sex and head size are regressed out of all data before computing the correlations. Maximum $r^2 = 0.045$. See Online Methods for more details of these analyses. (**h**) Plot relating all 14 T2* IDPs to 1100 non-imaging variables. Maximum $r^2 = 0.034$.

Group-averaged diffusion MRI atlases are shown in **Fig 2**. dMRI data reflects the random diffusion of water molecules as restricted by local tissue microstructure[21]; in white matter this results in orientation dependence of water movement due to hindrance to diffusion perpendicular to the long axis of axonal fiber bundles. The diffusion signal was analyzed both to infer the local density of membranes/neurites, and traced from voxel to voxel ("tractography") to derive macroscopic white matter pathways. Three complementary diffusion models were fit to the signal in each imaging voxel: (i) a diffusion tensor model[22] was fit, describing the signal phenomenologically as resulting from a 3D ellipsoid profile of water displacement; (ii) the neurite orientation dispersion and density imaging (NODDI) model[23] was applied, to estimate microstructural properties (e.g. neurites vs extracellular space); and (iii) the ball & sticks model[24] was used to estimate the orientation of multiple fiber populations within a voxel for tractography. 675 IDPs were extracted, by averaging parameters estimated by the first two models over 75 different white-matter tracts defined based both on subject-specific tractography[25, 26] and from population-average standard white matter skeleton masks[27, 28].

Figure 2 The diffusion MRI data in UK Biobank. (**a**) Group-average (n≈4500) atlases from six distinct dMRI modeling outputs, each sensitive to different aspects of the white matter microarchitecture. See Online Methods for more processing details. The atlases shown are: FA (fractional anisotropy), MD (mean diffusivity) and MO (tensor mode) from a tensor fit to the b=1000 shell only; ICVF (intra-cellular volume fraction), ISOVF (isotropic or free water volume fraction) and OD (orientation dispersion index), from the NODDI microstructural modeling of the full dMRI data. Also shown are several of the standard-space white matter skeleton masks applied to the dMRI data used to generate IDPs (e.g., pink are retrolenticular tracts in the internal capsules; upper-green is the superior longitudinal fasciculi). (**b**) Tensor glyphs depicting the group-averaged tensor fit at each voxel for the region shown in the inset in (c). The size of the displayed ellipsoids indicate the strength of water diffusion along three principal directions. Long thin tensors indicate single dominant fiber bundles, whereas more spherical tensors (within white matter) generally imply regions of crossing fibers (clearly seen to be explicitly modeled in corresponding parts of (c)). (**c**) Group-averaged multiple fiber orientation atlases, showing up to 3 distinct fiber populations modeled per voxel. Red shows the strongest fiber direction, green the second, and blue the third. For each fiber population the direction is only shown where the probabilistic modeling estimates greater than 5% voxel occupancy. Inset shows the thresholded FA image (copper) overlaid on the T1, with the region shown in detail in (b) and c) highlighted. (**d**) Four example group-average white matter tract atlases estimated by probabilistic tractography fed from the within-voxel fiber modeling: corpus callosum (genu), superior longitudinal fasciculus, corticospinal tract and inferior fronto-occipital fasciculus. Masks derived from these tracts are applied to the various dMRI modeling outputs to generate additional IDPs. (**e**) Plot relating all 675 dMRI IDPs (nine distinct dMRI modeling outputs from tensor and NODDI models × 75 tract masks) to 1100 non-imaging variables (see **Fig 1g** for details). Maximum $r^2 = 0.057$.

Group-averaged results from the functional MRI data are shown in **Figs 3** and **4** (task and resting-state fMRI respectively). This data reflects neural activity indirectly, based on the dynamic changes in blood oxygenation and flow resulting from changes in neural metabolic demand[29, 30]. The task (viewing shapes and emotionally negative faces[31]) was chosen to engage a range of neural systems, from low-level sensory and motor to perceptual (e.g., fusiform) and emotional (e.g., amygdala) areas. The 16 tfMRI IDPs quantitate the strength of brain activity changes for specific aspects of the task, in regions defined using the group-averaged template activation maps shown, in three task conditions. Processing of the rfMRI data (see Online Methods for details) identified functional brain networks[32]. In brief, group analysis of the rfMRI data generates two atlases of these functional networks - a "low-dimensional" decomposition of the brain into 21 functional sub-divisions and a higher-dimensional parcellation into 55 sub-divisions. These sub-divisions are often referred to as "network nodes" and the connections between them as "network edges". IDPs represent a) edge connectivity strengths

and b) node fluctuation amplitudes (1695 IDPs, **Fig 4**). In **Supplementary Fig 1** we show group-averages of the default mode network derived from varying group sizes (15 to 5000); it is clear that background noise is increasingly suppressed, without any increase in network map blurring, at the highest subject numbers. It is also shown that voxelwise estimates of age-dependence in this cognitive network stabilize with increasing numbers, and statistical significance rises.

Figure 3 The task fMRI data in UK Biobank. (**a**) The task paradigm temporal model (time running vertically) depicting the periods of the two task types (shapes and faces). (**b**) Example fitted activation model vs timeseries data (time running horizontally), for the voxel most strongly responding to the "faces > shapes" contrast in a single subject (Z=12.3). (**c**) Percentage of subjects passing simple voxel-wise activation thresholding (Z>1.96) for the same contrast. Note reliable focal activation in left and right amygdala. The underlying image is the group-averaged raw fMRI image. (**d**) Group-averaged activation for the 3 contrasts of most interest, overlaid on the group-average T1 atlas. (**e**) Instructions for the task shown to participants in the scanner, including example shape and face images. (**f**) Plot relating the 16 tfMRI IDPs to 1100 non-imaging variables (see **Fig 1g** for details). Maximum $r^2 = 0.018$.

Figure 4 The resting-state fMRI data in UK Biobank. (**a**) Example group-average resting-state network (RSN) atlases from the low-dimensional group-ICA, showing four out of 21 estimated functional brain networks, including the default mode network (red-yellow), dorsal attention network (green), primary visual (copper), and higher level visual (dorsal and ventral streams, blue). The three slides shown are (top to bottom) sagittal, coronal and axial. (**b**) The 55 non-artefact components from a higher-dimensional parcelation of the brain (axial views). These are presented as displayed by the interactive connectome browser (http://www.fmrib.ox.ac.uk/analysis/techrep/ukb/netjs_d100), allowing interactive investigation of individual connections in the group-averaged functional network modeling. The 55 brain regions (network nodes) are clustered into groups according to their average population connectivity, and the strongest individual functional connections are shown (positive in red, anticorrelations in blue). (**c**) Plot relating the 76 rfMRI "node amplitude" IDPs to 1100 non-imaging variables (see **Fig 1g** for details). Maximum $r^2 = 0.065$. (**d**) Plot relating the 1695 rfMRI "functional connectivity" IDPs to 1100 non-imaging variables. Maximum $r^2 = 0.032$.

Voxel-wise associations with aging

IDPs aim to be a useful reduction of raw data into a compact set of meaningful measures of brain function and structure. The first set of IDPs that we derived condenses ~2GB raw data per subject into 2501 IDP values. However, these summary measures can lose valuable information. After preprocessing to align images to common coordinate systems, the data in UK Biobank can be analysed for cross-subject variations at the voxel level. This provides a more spatially-detailed exploration of the richness of the imaging data than can be achieved via IDPs, but requires greater imaging expertise and computational resources, as well as often leading to lower statistical power (both because of the greatly increased number of multiple comparisons that need to be accounted for, and because of the higher noise associated with voxel-wise measures compared with the IDP summary measures that combine across many voxels).

Fig 5 presents voxel-wise correlations of age with several of the parameters modeled from the diffusion MRI data along the centers of the main white matter tracts, as well as normalized T2 FLAIR intensity in the white matter. **For the** dMRI measures, Bonferroni correction across voxels results in significance at a threshold of approximately r=0.1 (n=3722). The dMRI-derived quantity that is most commonly used in cross-subject analyses is fractional anisotropy (FA, **Fig 5a**), a sensitive (though biologically non-specific) marker of general white matter integrity. The predominant pattern seen here is the expected reduction of FA with aging (see histogram in **Fig 5g**); however, some areas show FA increases, likely due to degradation of secondary fibers or reduction in fiber "fanning"[33]. These significant positive correlations are notable given that none of the FA-based IDPs exhibit a significant positive correlation, where the latter represent the average FA across the extent of specific tracts. Another quantity estimated from the dMRI data is the tensor mode (**Fig 5b**), which primarily describes whether a white matter voxel is dominated by one vs. multiple fiber populations. Here, tensor mode was even more sensitive to the differential effect (seen in FA) with aging[33], in particular in certain association fibers and posterior corpus callosum (arrows). Other parameters are sensitive to distinct effects, such as the increase in free water with aging (**Fig 5d**); the strongest increase, seen in the fornix (arrow), is likely due to the increased partial volume effects associated with measures of this thin tract because of greater cerebrospinal fluid due to age-related atrophy (i.e., a lower fraction of white matter and larger fraction of fluid). Finally, we calculated voxel-wise cross-subject correlation with age after normalizing the T2 FLAIR images to have the same median white matter intensity in all subjects. This analysis identified peri-ventricular areas that are most susceptible to developing white matter hyperintensities ("lesions") in the population (**Fig 5e**; r>0.1, n=3781). In studies involving much smaller numbers of subjects, it is typical to either smooth the data, or use test statistics that spread information across multiple voxels in order to achieve the statistical power needed to find significant results, in either case resulting in a loss of spatial specificity compared with the voxel-wise tests carried out here without data smoothing.

Figure 5 Voxel-wise correlations of participants' age against several white matter measures from the dMRI and T2 FLAIR data. (**a**) Voxel-wise (cross-subject) correlation of FA (fractional anisotropy) vs. age. Group-average FA in white matter is shown in green, overlaid onto the group-average T1. Blue and red-yellow show negative and positive correlation with age, respectively (P<0.05 corrected). (**b**) Correlation of MO (tensor mode) vs. age, using the same color scheme as in (a). Areas of MO increase are shown in greater detail in (**f**), which also shows the distinct primary fiber directions. (**c**) Correlation of OD (orientation dispersion) vs. age, including a reduction in dispersion in posterior corpus callosum. (**d**) Correlation of ISOVF (isotropic or free water volume fraction) vs. age, showing increases in "free water" with age in a broad range of tracts. (**e**) Voxel-wise correlation of T2 FLAIR intensity, showing increased intensity with aging in white matter. (**g**) Histograms (across voxels) of the voxel-wise age correlation of the correlation maps shown above, with correlation value on the *x* axis. FA and MO largely decrease with age, while OD and ISOVF largely increase.

Pairwise associations between brain IDPs and other measures

We conducted simple univariate association analyses in order to illustrate the richness of relationships between the extracted brain IDPs and the many other types of variables recorded by UK Biobank, as well as the statistical power afforded by around 5000 subjects' datasets. We correlated all 2501 brain IDPs (individually) with 1100 other Biobank variables (see Manhattan plots in **Figs 1-4, Fig 6, Supplemental Fig 2**, and Online Methods for more details). With this large number of subjects, even after multiple comparison correction for these 2.8 million correlations, most classes of variables showed significant associations with most brain imaging modalities. For example, using FDR (false discovery rate) correction, 57 out of 66 combinations of modalities and categories of non-imaging phenotype show significant associations. Some classes of variables exhibited large numbers of associations with IDPs (in particular the general physical measures such as height and weight), whereas others (such as cognitive measures, and alcohol and tobacco lifestyle measures) had a more focused set of associations. These associations were estimated after adjusting all variables for effects of age, sex, head motion and head size. Whereas some factors (e.g., head motion, which can corrupt IDPs but also correlates with disease/age[34]) were likely to be unambiguously considered a confound to be removed, for other factors (e.g., age) the appropriate analysis can depend on the question being asked.

Figure 6 Visualisation of 2.8 million univariate cross-subject association tests between 2501 IDPs and 1100 other variables in the UK Biobank database. (**a**) Manhattan plot showing, for each of the 1100 non-brain-imaging variables, the statistically strongest association of that variable with each distinct imaging sub-modality's IDPs. (i.e., 6 results plotted for each x axis position, each with a color indicating a brain imaging modality; this plot differs from the other Manhattan plots, which show correlations with all IDPs). Whereas the Manhattan plots in **Figs 1-4** indicated associations for each brain imaging modality separately, here we depict all associations in a single plot. (**b**) List of all IDP-cognition associations passing Bonferroni correction for multiple comparisons. The first column lists the correlation when age is adjusted for, and the second shows the unadjusted correlation. UK Biobank cognitive tests carried out include Fluid Intelligence, Prospective Memory, Reaction Time (Shape Pairs Matching), Memorised Pairs Matching, Trail Making (Symbol Ordering), Symbol Digit Substitution, and Numeric Memory. (**c**) IDP associations with the cognitive phenotype variables (the full set of 174 cognitive variables, repeated for each brain imaging modality). Shown behind, in gray, are the same associations without adjustment for age, with a large number of stronger apparent associations. (**d**) For all univariate associations shown here and in previous figures, data are adjusted for several effects (age, sex, age-sex interaction, head motion, head size). This scatterplot shows the relationship between these correlations and those obtained without first regressing out these variables (each point is a pairing of one IDP with one non-brain-imaging variable, with 2.8 million points in the scatter plot). The grid lines indicate Bonferroni-corrected significance level. This shows that in almost all cases, the strength of association was reduced by adjusting for age, sex, head size and head motion (as reflected by the shallow slope of the scatter on these equally-scaled axes). In a minority of cases (horizontal cloud around y=0) the association was almost entirely removed by this "de-confounding". (**e**) Association between unadjusted white matter volume and fat-free body mass is high (r=0.56) when pooling across the sexes. After adjusting for several variables (including sex), the correlation falls almost to zero.

As an example of a focused association study that might be conducted, we considered the associations between cognitive tests and brain IDPs, and investigated potential age interactions in these associations. In all cases, sex, amount of head motion, and head size were regressed out of all data before computing correlations (see Online Methods for more details of preprocessing for association tests). Bonferroni-significant ($P<1.8\times10^{-8}$) associations with brain IDPs, after adjusting for age, are shown in **Fig 6b** and are discussed briefly below. This set of significant associations was also evaluated without first regressing age out of IDPs and test scores (see the second column of correlations in **Fig 6b**). The task-fMRI vs Fluid Intelligence associations are unchanged by including age in the correlations, whereas all other cognition-IDP correlations are significantly stronger (P<0.005 corrected) if age is not adjusted for, approximately doubling the strengths of associations.

In the Symbol Digit Substitution test, participants replace symbols with numbers using a substitution key provided. The two scores from this test with strong IDP associations were *Number of symbol digit matches made correctly* and *Number of symbol digit matches attempted* (in the time allowed). As this is primarily a speed test, with symbol substitutions rarely incorrect, these two scores are highly correlated with each other (r=0.97). These scores correlated negatively with measures of water diffusivity in several tracts: superior and posterior corona radiata, and superior thalamic radiation. These IDPs include both average diffusivity (across all

directions) and L1, which measures diffusivity along the direction of fastest diffusion (generally corresponding to dominant white matter fiber orientation). Additionally, these test scores correlate with FA (fractional anisotropy) in the posterior fornix (a result consistent with literature[35]). While FA is often referred to as reflecting integrity of axonal fibers, for thin tracts like the fornix it is also sensitive to variations in tract thickness[36]. Finally, there is a significant association with thalamus volume consistent with literature[37] (while only right thalamus volume passes the Bonferroni test, left thalamus volume is almost as highly correlated with the cognitive score, r=0.10). The sign of these effects all correspond to lower cognitive performance correlating with aging and pathology (as reflected by increased diffusivity and atrophy)

In the Reaction Time test, subjects confirm whether two abstract symbols match as quickly as possible. *Mean time to correctly identify matches* was found to correlate inversely with left putamen volume, a result consistent with[38]. Right putamen volume correlates at a similar level (r=-0.06) but does not quite reach Bonferroni significance. The sign of the correlation indicates increased subcortical structure volume correlating negatively with mean response time (i.e., positively with cognitive speed).

The Fluid Intelligence score reports how many of a range of numerical, logic and syntactic questions subjects were able to answer in two minutes. This score was negatively correlated with strength of grey matter activation in the simple shapes matching task carried out during the imaging. This negative correlation may seem surprising. However, the shapes matching task used in the task-fMRI is much less cognitively demanding than the Fluid Intelligence task, and it is plausible that participants with higher intelligence could carry out shape matching in a way that requires lower levels of neural activity, a mechanism that has been reported previously and ascribed to "minimization of cognitive workload"[39, 40]. Given that these associations show no age interaction (unlike those above), it seems unlikely that the cross-subject variance driving this result relates to age-related alterations in neuro-vascular coupling[41] or cognitive reserve[40].

All associations found involve cognitive processing speed as a significant factor, which is consistent with previous studies that found processing speed to be the strongest cognitive factor with white matter associations[35]. However, the observation that the different test scores do not all correlate identically with each other or with the same brain IDPs suggests that there is not a single (speed-related) cognitive factor at play in these associations.

The observation that most of the associations doubled in strength when not removing age effects suggests that age-related cognitive decline is a significant source of cross-subject variability of high relevance for these IDP-cognition associations[36]. This can be seen further from the complete set of IDP-cognitive associations (**Fig 6c**), in which a large number of non-age-adjusted associations (grey circles) were stronger than the results after age adjustment (colored circles). Such interpretations can be aided further through appropriate multivariate analyses, and we revisit this in the following section. These age-interaction results raise the expectation that the associations already seen in the first 5000 participants will lead to cognitive biomarkers that should be predictive of pathologies relevant to cognition, once such clinical outcomes starts to manifest in the cohort over coming years.

Multivariate associations between brain IDPs and other measures: dominant modes of population variation

We conducted multivariate analyses of the IDPs and non-imaging variables using canonical correlation analysis (CCA[42]) combined with independent component analysis (ICA[43]) (**Figs 7-8** and **Supplementary Figs 3-7**). This analysis identifies "modes" of population covariation linking IDPs to non-imaging measures. Each mode consists of one combination of IDPs and non-imaging measures that all have a highly similar variation across the set of subjects. The relative strength of involvement of a particular variable in a given mode is dictated by the variable weight, as shown in the first column in **Fig 7**. Multiple population modes may be identified, provided they describe different (independent) aspects of cross-subject variation, meaning that the implied association between a given pair of variables can vary from mode to mode. Similar methodology was recently able to identify a single statistically-significant mode of population covariation between IDPs and non-imaging measures in 461 young healthy adults in the Human Connectome Project (HCP) dataset[15, 44].

From the current UK Biobank release, we identified nine modes that were highly significant ($P_{corrected}<0.002$). This increase in population modes between HCP and Biobank likely relates to the tenfold increase in the number of subjects, a much larger number of non-imaging variables, and having subjects spanning a broader and older age range. While these modes are not guaranteed to reflect biological processes and/or life factors of interest, in practice ICA has proven adept at identifying modes with such interpretability[45, 46]. Of the nine modes found in our analysis, some were relatively simple reflections of dominant physical factors such as body size or heart rate, while others were more complex, linking rich subsets of non-imaging measures (biophysical, early life and lifestyle) to imaging measures (brain morphology, microstructure, and functional or structural connectivity).

Modes 1-6 are displayed and briefly described in **Supplementary Figs 3-7.** Modes 7-9 are displayed in **Fig 7**, with modes 7 and 9 discussed in more detail below, continuing our focus on the relationship between IDPs and Biobank's cognitive tests.

Figure 7 Details of three modes from the doubly-multivariate CCA-ICA analyses across all IDPs and non-brain-imaging variables. IDPs are listed in orange and non-brain-imaging variables in black. The text lists show the variables most strongly associated with each mode; where multiple very similar (and highly correlated) non-imaging variables are found, only the most significant is listed here for brevity. The first column shows the weight (strength and sign) of a given variable in the ICA mode, the second shows the (cross-subject) percentage variance of the data explained by this mode, and the third column shows the percentage variance explained in the data without the confounds first regressed out. Mode 7 links measures of bone density, brain structure/tissue volumes and cognitive tests. Mode 8 links measures of blood pressure and alcohol intake to IDPs from the diffusion and functional connectivity data; two functional network connections strongly involved are displayed, with the population mean connection indicated by the bar connecting the two nodes forming the connection (red indicates positive mean correlation, blue negative, and the width of the bar indicates the connection strength). Mode 9 includes a wide range of imaging and non-imaging variables (see main text for details); as well as showing 3 strong functional network connections, we also show two functional nodes whose resting fluctuation amplitude is associated with this mode.

Figure 8 Associations of the nine CCA-ICA modes with confounds and other variables of interest. (a) Associations (correlations and regressions) of the nine CCA-ICA modes against the confound variables that were regressed out of the data prior to the CCA-ICA analysis. For example, modes 1,2,4,5,7,8 are associated with aging, whereas 3,6,9 are not strongly associated with age. (b) Correlation of the CCA-ICA modes against several variables of interest, including some clinical outcomes. (c) Scatterplot of CCA-ICA modes 1 vs. 8 (one point per subject), showing the associations between these modes, age and sex. Colors running from green to red indicate increasing age in females; colors running from blue to pink indicates increasing age in males.

Mode 7 is one of two modes that includes significant contribution from the cognitive tests. It primarily links bone density measures and cognitive scores to brain structure/tissue volumes and diffusion MRI measures. There is extensive literature linking the volume and diffusivity measures identified in this mode to cognition, but a relationship between these measures and bone density has not to our knowledge been reported. This link could therefore reflect variations in physical properties of non-interest that are not fully accounted for by the applid de-confounding. However, there is existing evidence for a correlation between low bone density and accelerated cognitive decline[47, 48] including bone density as a risk factor for Alzheimer's disease[49, 50], which may relate to hypothalamic regulation of bone density[51] and the compromise of this deep brain structure in early AD[52]. Therefore, this mode may be identifying patterns in the population that relate to known relationships between bone density and cognitive decline of relevance to neuropathology.

The most complex population pattern was found in mode 9 (**Fig 7c**), where the non-imaging variables spanned a diverse range. including physical and dietary lifestyle factors. The most strongly-involved were intelligence, education levels and occupational characteristics. Some of the more apparently obscure lifestyle factors may reflect socio-economic status as a latent factor (e.g., cheese intake or time spent outdoors in winter, which have strong weights in this mode). The brain IDPs include task fMRI (with a negative weight, consistent with the sign of association between these IDPs and the cognitive scores, discussed above) followed by a range of functional and structural IDPs. Interestingly, there is some overlap between modes 7 and 9 in terms of cognitive tasks (symbol digit matches), bone density and T1-based brain volumes, although there are also significant differences in both IDPs and non-imaging measures in the two modes. Moreover, the fact that CCA-ICA separated modes 7 from 9 indicates that they constitute distinct biophysical patterns of variation across subjects; for example, as discussed below, mode 7 relates strongly to subject age while mode 9 does not. The broader range of non-imaging measures involved in mode 9, and the ability to interpret many of them in terms of positive or negative life factors, is reminiscent of the single mode previously reported from HCP data[15, 44]. That previously reported mode had some correspondence to the long-standing observation of strong correlations between a broad range of cognitive and behavioural tests (the "general intelligence" factor), but also extends beyond cognition to include demographic and life factors. However, there is not perfect correspondence between mode 9 reported here and the previous HCP mode. This may be due to key differences in the HCP and Biobank datasets, including different non-imaging measures, the use of only functional connectivity in the HCP analysis, the different cohort profiles (e.g., age range) and/or the ability to separate more modes from the larger Biobank cohort.

These multivariate analyses were interrogated with respect to their relationship to both potential confounds and variables of interest (**Fig 8**). As with the univariate analyses, data fed into the multivariate analyses were first adjusted for parameters that might otherwise induce apparent relationships based on non-interesting factors (age, sex, head size, head motion). **Fig 8a** shows how, by projecting the CCA-ICA modes back onto the original data, we can estimate how strongly the discovered modes relate to these parameters. Interpretation of the population modes was therefore aided by noting that modes 1,2,4,5,7,8 were strongly associated with aging, whereas 3,6,9 were not. Considering this in the light of the fact that all data input to the CCA had been age-adjusted suggests that, while these modes reflect meaningful biological processes related to aging, their

identification here was not driven by trivial corruption of IDPs by aging (e.g., reduced FMRI signal due to cortical thinning). Similarly, individual modes could be interrogated with respect to their relationship to specific variables of interest (**Fig 8b**), including clinical outcomes (for which, at this stage, numbers are naturally quite limited).

DISCUSSION

Data analysis in population imaging

The analyses presented here demonstrate some of the possibilities offered by the UK Biobank imaging resource, particularly relating to the size of the cohort. A wide range of analysis methods could be applied to UK Biobank imaging data (including some of the approaches used in example analyses included above). The simplest, very focused association studies may select just two variables to investigate, for example one summary imaging measure (such as total gray matter volume), correlated against one life factor, genetic marker, physical assay or health outcome (such as development of Parkinson's disease). A slightly more complex analysis would consider a larger number of variables to model simultaneously – for example, looking to predict health outcome from linear multiple regression against a few predictor variables such as some imaging measures and some genetic markers. One natural extension of this is to attempt to predict, for example, a particular health outcome as a linear combination of many thousands of other variables; this would probably no longer be a simple linear multiple regression, due to potentially having more predictor variables than samples (subjects); hence some form of penalized regression (and/or data-driven variable pre-selection) would likely be necessary[32]. Another natural extension of a limited linear multiple regression would be to look for nonlinear interactions between predictor variables, for example considering an imaging measure, a life factor and an interaction term between the two as three distinct predictors. An even more complex analysis might replace the single outcome variable with multiple variables, hence looking for "doubly-multivariate" associations between two or more sets of variables (the CCA-ICA analyses presented above are an example of this). Finally, other analyses may utilize imaging measures as proxies for healthcare outcomes (for example, on the basis of prior studies or analyses using UK Biobank data), potentially because imaging markers are more sensitive or more specific than clinical symptoms[53]. The ability to achieve improved sensitivity/specificity could, for example, arise if imaging reflects biological processes underlying disease mechanisms more accurately than downstream symptoms, enabling clustering of patients that is more predictive of prognosis or therapeutic response[54].

Pairwise correlation analyses result in simple outcome measures, although interpretation nevertheless requires an understanding of the caveats in imaging-derived measures. Data-driven multivariate analyses, which aim to discover associations between sets of multiple variables, have complementary benefits, including increased sensitivity to biological processes that are reflected in multiple correlated variables. A small number of dominant population patterns of association can be much easier to interpret compared with millions of univariate associations. The ability of multivariate analyses to tease apart distinct biological processes with potentially opposing relationships between variables[55] is a significant advantage over univariate correlation analyses. For example, mode 4 revealed one aging-related process that also involved changes in heart rate and rfMRI amplitudes and functional connectivity, which was separated out from mode 8, another aging-related process that also involved blood pressure and white matter microstructure. These processes may well be biologically distinct, reflecting different internal and external driving factors, whereas a simple correlational analysis (such as that described in the previous section) would show associations between all factors, including even those (such as functional connectivity and white matter changes) that appeared in separate modes. Additionally, as in multiple regression, simultaneous identification of multiple modes of association reduces the unexplained residual variance (effectively data "de-noising")[56].

Multivariate analyses of multi-modal data like UK Biobank enables discovery of (potentially complex) clinical phenotypes. This is particularly powerful when traditional diagnostic categories rely on clinical symptoms that do not map cleanly onto underlying disease mechanisms. Discovering relevant population axes and sub-groups based on imaging, genetics and other objective markers is expected to profoundly increase our understanding of the etiology and pathogenesis of a wide variety of common and rare diseases; for example, this concept is at the heart of the recently-proposed Research Domain Criteria (RDoC) in psychiatry[54]. A tenet here is that for many complex diseases (such as schizophrenia), there is wide belief that better disease understanding will require the discovery of distinct mechanisms/sub-diseases that are currently conflated, but that such sub-group discovery is unlikely to occur solely through symptom-based investigations.

Challenges of population imaging

UK Biobank data is openly available to researchers from a broad range of backgrounds, including non-imaging experts. However, the imaging data is considerably more complex than most of the already-existing UK Biobank measures. Extensive post-processing is required to align image voxels across subjects and remove artefacts.

Moreover, information in images is usually encoded across multiple voxels, requiring further processing to extract relevant features. MRI modalities are generally indirect measures of the biology of interest. Even apparently straightforward measures like structural atrophy are susceptible to misinterpretation[57]; functional MRI signals can reflect vascular pathology or alterations in neuro-vascular coupling rather than activity[41]; and diffusion MRI is sensitive to a broad range of changes to tissue microstructure[21]. Finally, data sizes have become extremely large, requiring algorithms and approaches capable of handling truly "big data": the unprocessed brain imaging data in UK Biobank totals 2GB per subject, totalling 0.2PB for all 100,000 subjects when these data acquired, even before data inflation during post-processing.

Large cohorts face the further challenge that statistically significant associations are identified even when their explanatory power is small. In the present dataset, even after correcting for millions of multiple comparisons, significance is reached at a correlation of just $r \approx 0.1$, i.e., 1% of population variance explained[58]. This is well known in large genome-wide association studies (GWAS), where it is accepted that small effect sizes may still be important, partly because multiple determinants can combine to create a large effect. However, in the case of GWAS, for which genetic variants can be interpreted as markers of causal factors (whether direct or indirect[59]), apparent associations across IDPs and non-imaging phenotypes could result from a shared latent (non-measured) causal factor. For example, education level could easily result in a given dietary factor appearing to be associated with a brain IDP, despite no causal connection between the diet and IDP. This danger is higher with large subject numbers due to increased significance, but may in the case of UK Biobank be mitigated due to the very large number of measured life factor and biological variables. While the population variances explained in the pairwise associations reach maxima of only around 5% (**Supplementary Fig 2**), these can be much higher with the multivariate analyses presented above (up to 20-50% variance explained in the most highly involved variables within the population modes). This reflects not just the increased sensitivity gained when appropriately combining across related variables, but also the effective "denoising" achieved by modeling multiple population effects simultaneously.

The importance of accounting for subtle confounds when using IDPs is exemplified in **Fig 6d**, which shows an apparent association between total white matter volume and fat-free body mass (one scatter point per subject). Without any adjustments/de-confounding (left plot), there is an extremely strong correlation between these variables. However, this association is largely driven by the average differences in body mass and head size between sexes (see color coding). After adjusting for sex, age and head size, the association disappears (right plot). This is an example of Simpson's paradox[60], in which suboptimal pooling across groups of variables (sex) results in a misleading association. Other potentially misleading analysis scenarios include failing to consider study population selection bias[61], and inappropriate adjustment for variables that are caused by (but not feeding into) the variables of interest[62]. While there can be no guarantee that the set of participants in UK Biobank is an unbiased sample of the full population, that does not imply that studies using the data have to retain the same biases (though again it is still possible for bias to arise[61]); indeed, one important aspect of future study design will be the selection of Biobank subjects to feed into an analysis. In the case of focused hypothesis testing, it is likely that carefully selected sub-groups of subjects should be utilized. For example, once a group of subjects is identified to have a particular clinical diagnosis, it is likely that optimal sensitivity and interpretability will be achieved by comparing their data not against all other subjects in the database, but against a matched control group having as many relevant factors (sex, age, relevant life factors not appearing in the predictive model, etc.) carefully matched against the clinical "case" group.

Future studies might seek to find causalities between variables, for example using structural equation modeling, Bayes Nets or non-linear/non-Gaussian methods[63]. The dangers of inferring causalities from observational datasets (such as UK Biobank) are well-known; the inclusion of genotype data (and other measures that might be considered "instrumental") may be of value through analyses such as Mendelian randomization, although important caveats must be considered[59]. The safest way to confirm causal results discovered from such observational datasets is to use such results to form hypotheses for new focused interventional studies.

The mapping of disease associations and population patterns (e.g., learned from UK Biobank data) onto individuals in the future will be an important long-term goal. For example, population distributions of imaging measures and health outcomes can be learned, and be used to form patient-specific prior distributions to combine with measures from a new patient. While this might not provide statistical certainty for a diagnosis or recommended treatment, it should allow for single-patient imaging to be used in a way that is currently just beginning for the most advanced uses of patient-tuned genetic testing.

Population imaging landscape

In the early 2000s, a number of ambitious studies set out to image group sizes in the low thousands of subjects[3-7]. There are now a few new brain imaging studies that are aiming to image tens of thousands of subjects, including the Maastricht Study (n=10,000)[8], the German National Cohort (n=30,000)[9] and the Rhineland Study (n=30,000). In addition to even larger numbers than these, UK Biobank imaging benefits from the breadth of organ systems

imaged, the highly multi-modal brain protocol, and the existing phenotyping and genetics. The Rhineland and GNC studies will incorporate a longitudinal component, which is also planned for a subset of the imaging participants in UK Biobank. The GNC, Rhineland and Biobank studies have each adopted the approach of purchasing identical MRI scanners at a small number of dedicated sites, with the goal of making data maximally homogeneous within study. A major challenge to further leverage these large datasets is to develop analysis tools that can harmonize data across these studies, given that imaging protocols for each study are necessarily tailored to different constraints. Whereas harmonization of smaller cohort studies requires the inclusion of a large number of diverse imaging protocols, there could be considerable impact in focusing on harmonization of a few very large cohorts (e.g., to combine data from UK Biobank and the Rhineland study).

Even with just 5% of the eventual cohort size, our results presented here demonstrate the statistical benefits that are conferred by very large number of subjects, where statistical significance scales exponentially with subject numbers. However, the primary rationale for the size of the study is not to boost statistical power across 100,000 datasets, but rather to provide prospective imaging data suitable to discover early markers and risk factors for as broad a set of diseases as possible, both rare and highly prevalent. For some rare diseases with few established risk factors, only these large numbers will allow discovery of pre-symptomatic markers; for example, 50-100 participants are expected to develop sporadic amyotrophic lateral sclerosis (ALS) by 2027. This rich imaging addition to the ongoing UK Biobank study will allow scientists to discover novel insights into the causes of brain disease, provide markers with predictive power for therapeutic interventions, and advance non-invasive imaging-based screening for preventative healthcare.

Contributions

KLM, RC, PMM and SMS provided the overall scientific strategy for UK Biobank brain imaging; KLM, NKB, DLT, EY, JX, AJB, SJ, SNS, JLRA, MJ, PMM and SMS developed acquisition protocols; NKB, KLM, TWO, PW, ID, SG and SH implemented the imaging protocol at the dedicated imaging centre; FAA, KLM, SJ, SNS, JLRA, LG, GD, MJ and SMS developed post-processing pipelines and IDP calculation; KLM and SMS carried out the univariate/multivariate analyses and prepared figures; KLM and SMS wrote the manuscript, which was edited by all authors.

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ONLINE METHODS

Protocol Overview

Imaging protocols were designed by the UK Biobank Imaging Working Group (www.ukbiobank.ac.uk/expert-working-groups), in consultation with a large number of brain imaging experts (listed in the acknowledgments). MRI provides many imaging modalities offering complementary information. As part of this consultancy, a number of modalities were determined to be infeasible or lower priority for a range of reasons. Considerations included time constraints, generalizability, feasibility of automated analysis, and existence of robust, well-tested acquisition methods. The advisory network therefore decided not to include quantitative relaxometry, MR spectroscopy or angiography. Arterial spin labeling is currently being piloted, as described below.

To maximize data compatibility, three dedicated imaging centers will have identical scanners with fixed platforms (i.e., no major software or hardware updates throughout the study). Each center is equipped with a 3T Siemens Skyra (software platform VD13), 1.5T Siemens Aera (VD13), carotid ultrasound and dual energy X-ray absorptiometry (DEXA). Brain imaging is being conducted on the 3T system using a 32-channel receive head coil.

Key acquisition parameters for each modality are summarized in **Supplemental Table 1**, grouped according to primary modality categories (structural, diffusion and functional MRI). Order of acquisition was optimized in consideration of subject compliance, assuming subject motion might increase over the scan (favoring early acquisition of the T1 due to its central importance – for example the processing pipeline cannot run without the T1) and subject wakefulness might decrease (favoring early acquisition of fMRI). The order is: (1) T1, (2) resting fMRI, (3) task fMRI, (4) T2 FLAIR, (5) dMRI, (6) swMRI.

Further protocol details are available at: http://biobank.ctsu.ox.ac.uk/crystal/refer.cgi?id=2367 and further description of post-processing pipelines and data outputs included in the first data release are available at: http://biobank.ctsu.ox.ac.uk/crystal/docs/brain_mri.pdf. All software used in these pipelines is freely available[64, 65] and full pipeline processing scripts will shortly be publicly available.

The processing pipeline utilized for the initial data release was primarily based on tools from FSL (the FMRIB Software Library[64]), but it will be gradually expanded to utilize a broader range of methods and software, where this will increase the quality, robustness and scope of IDPs generated. For example, one high priority is to adapt the Human Connectome Project pipelines[66] to provide cortical surface modeling.

The intention is that non-imaging experts will be able to use the IDPs directly without having to become expert in the complexities of data processing, although we encourage engagement with imaging experts in light of the numerous and subtle caveats and confounds associated with interpreting these data.

Data access requests from all academic or commercial researchers (with no exclusive or preferential access) are processed by the UK Biobank's Research Access Administration Team and approved relatively rapidly provided that they fulfill UK Biobank's aims of supporting health research in the public interest. Researchers' institutions then sign a Material Transfer Agreement agreeing not to attempt to identify any participant, and to return any derived data (e.g., new IDPs) to UK Biobank, to be made available to other approved researchers after an agreed "embargo" period (to allow findings to be published or IP protected by the researchers). Thus, while the first set of IDPs described here from internally commissioned research is being made available immediately, the range of IDPs is expected to grow rapidly as additional contributions from the wider user community are added.

Protocol Considerations

Design of the brain imaging protocol was conducted through broad consultation with neuroimaging experts and required careful balance of a range of considerations, often specifically relating to the high throughput nature of UK Biobank. In setting up the pilot protocol, the primary challenge was to achieve the target of one participant scanned every 36 minutes without serious compromise to data quality compared to research protocols that might conventionally require up to an hour of scan time. Despite these tight time constraints, we aimed to include as many MRI modalities as possible, to take advantage of the full richness of information that can be provided by MRI. Here, we highlight the primary considerations that required a different approach from more conventional imaging studies.

- With each additional minute of scanning per subject effectively costing an additional ~£1million, there is enormous value associated with seemingly small efficiency savings. We recovered several minutes of scan time by systematically minimizing the overheads associated with subject placement, scan prescription, and calibration measurements. For example, changes to the shim settings and strict enforcement of a single shim

calibration harvested 2 minutes (changing system defaults to improve and accelerate shimming), which is equivalent to the scan time associated with some of the included modalities.

- Tight imaging FOVs (fields of view – the physical size of the imaged volume) are in general favorable to reduce scan time; however, these restrictions exclude subjects with larger heads or brains. For UK Biobank, even a "conservative" FOV that includes 99% of the population will exclude 1000 participants. As detailed statistics on brain size (as distinct from head size) were not available in the literature, we conducted a study of population brain size[67] that (in conjunction with optimal slice angling) enables our FOVs to target ≥99.9%.
- It is critically important that all analyses are automated. This translates to an additional role for certain imaging modalities beyond their intrinsic information content. Thus, although we considered methods for reducing scan time for T1-weighted structural scans while retaining coverage and resolution (e.g., elliptical sampling with consequent image blurring), this was deemed an unacceptable risk given the central role of the T1 to cross-subject and cross-modal alignment for most processing pipelines, including that implemented here for the initial data release.
- The EPI (echo-planar imaging) acquisitions for fMRI and dMRI result in significant image distortion that creates local misalignment in certain brain regions. Correction of this requires measurement of the magnetic field inhomogeneities that cause distortion. Two types of measurements are possible: a non-EPI gradient-echo acquisition with two echoes (conventional fieldmap) or two EPI-based spin echo acquisitions with opposite phase encode direction[68]. We chose the latter, which can be incorporated into the dMRI protocol as additional b=0 scans to reduce acquisition time (total acquisition time ~30s).
- To provide data with as rich and broad a range of applications as possible, we include imaging modalities that are not yet widely used in clinical practice, such as fMRI and dMRI. These modalities have demonstrated mechanistic and biological insights, and will hopefully see greater clinical take-up in the future, in part because of projects such as UK Biobank. We took advantage of recent advances in acquisition, largely developed as part of the Human Connectome Project, to obtain research quality data in limited time. Specifically, simultaneous multi-slice (or multiband, MB) acquisitions[69-72] that enable rapid fMRI and dMRI without sacrificing statistical robustness or directions/b-values[73], respectively. Without these accelerations, a seven-minute dMRI scan of the same spatial resolution would have been limited to ~32 directions and a single shell, precluding NODDI[23] and other more advanced biological modeling.
- After early piloting, a clinical T2/PD-weighted acquisition was removed from the protocol. This decision reflected to the limited relevance to UK Biobank goals (given the inclusion of the higher-quality and more biologically informative T2 FLAIR) and the value in recovering this scan time (just over 1 minute).
- One shortcoming of the current protocol is the lack of a direct measure of neurovascular health. We are piloting a protocol change to include a 2-minute perfusion scan (using arterial spin labeling). This would require reducing task fMRI to 2 minutes; while this is an extremely short task, early analyses (using truncated copies of existing initial tfMRI datasets) predict that it will be sufficiently robust.
- A major ethical question in studies of this nature relates to identification and handling of incidental findings of previously unknown pathology. The procedure to be followed in UK Biobank has been considered in great depth with major external ethical, legal and clinical radiology bodies, and with the funders and their external review group. An assessment of different approaches to the identification of incidental findings and the impact of their feedback on participants and the health service has been conducted as part of the pilot phase of UK Biobank's imaging project, and will be published separately. Based on its results and the deliberative process undertaken with external experts, the UK Biobank protocol for dealing with incidental findings does not involve the routine review of all scans for potential pathology by radiologists. Instead, if a radiographer incidentally identifies evidence of potentially serious pathology (i.e., likely to threaten life span, quality of life or major body functions) during the imaging process then a formal radiologist review is undertaken and, if it is confirmed as potentially serious, feedback is given to the participant and their doctor.
- Subjects are excluded from scanning according to fairly standard MRI safety/quality criteria, such as exclusions for metal implants, recent surgery, or health conditions directly problematic for MRI scanning, such as problems hearing, breathing or extreme claustrophobia.
- Once the second and third imaging centers are complete and running, UK Biobank will use non-human phantom objects and traveling volunteers to confirm quality and consistency across sites.

Structural Imaging

The T1 structural protocol is acquired at 1mm isotropic resolution using a 3D MPRAGE acquisition, with inversion and repetition times optimized for maximal contrast. The superior-inferior field-of-view is large (256mm), at little cost, in order to include reasonable amounts of neck/mouth, as those areas will be of interest to some researchers (for example, in the study of sleep apnea). Pre-processing of this modality included removal

of the face (which was deemed important to subject anonymisation for the standard data dissemination), brain extraction (removal of non-brain tissues from the image), linear alignment to the standard MNI152 brain template[74] and non-linear warping to this template[75] to maximize correspondence across individuals in light of significant cross-subject variation in brain structure. These alignments are used throughout the majority of the processing pipeline for other modalities.

T1 images are further analyzed to estimate volumes of a range of tissues and structures in each subject, which may reflect atrophy due to age and disease, as well as normal variation due to (e.g.) use-dependent plasticity. Images are segmented into tissue types (gray matter, white matter and cerebro-spinal fluid)[76]. Cortical gray matter volume is estimated, comparing the segmented gray matter to an atlas reference (where the external skull surface is used to normalize for head size)[77]. Sub-cortical volumes are estimated[78], utilizing population priors on shape and intensity variation across subjects. T1-based IDPs are generated for the volumes of major tissue types of the whole brain and for specific structures (primarily sub-cortically).

Too much reliance on spatial registration could limit the usefulness or accuracy of some IDPs. This is in part why many of the IDPs are in fact generated from within-subject analyses that do not depend on exact voxelwise spatial alignment to standard space (or between subjects): for example, 283 of the 715 structural and diffusion IDPs do not rely on exact spatial alignment and are carried out in the original space of each subjects' data.

The T2 protocol uses a fluid-attenuated inversion recovery (FLAIR) contrast with the 3D SPACE optimized readout[79]. This shows strong contrast for white matter hyperintensities. An automated pipeline for delineating these hyperintensities is currently being developed and future data releases will include IDPs reflecting the lesion "load".

The swMRI scan uses a 3D gradient echo acquisition at 0.8x0.8x3mm resolution, acquiring two echo times (TE=9.4 and 20 ms). Anisotropic voxels can enhance certain contrast mechanisms, particularly for vascular conspicuity due to through-plane dephasing effects, but are less ideal for other susceptibility-based processing. Ultimately, however, this choice was motivated by the desire for whole brain coverage in the face of very limited scan time (2.5 minutes). Signal decay times (T2*) are estimated from the magnitude images at the two TEs, and IDPs are reported as median T2* within the various subcortical regions delineated from the T1 processing. Venograms are generated through non-linear filtering of the magnitude and phase images[19], which produces enhanced conspicuity of medium and large veins. Automated segmentation of microbleeds and venograms would provide significant value, but to our knowledge robust tools for this are not yet available; future pipeline versions can hope to include such analyses. Future work will also consider whether this data will support quantitative susceptibility mapping, which would provide further information on tissue constituents as discussed in the main text.

Diffusion Imaging

Diffusion data is acquired with two b-values (b=1000 and 2000 s/mm^2) at 2mm spatial resolution, with multiband acceleration factor of 3. For each diffusion-weighted shell, 50 distinct diffusion-encoding directions were acquired (covering 100 distinct directions over the two b-values). The diffusion preparation is a standard ("monopolar") Stejskal-Tanner pulse sequence. This enables higher SNR due to a shorter echo time (TE=92ms) than a twice-refocused ("bipolar") sequence at the expense of stronger eddy current distortions, which are removed using the Eddy tool[80] (which also corrects for static field distortion and motion[81]).

Both diffusion tensor and NODDI models are fit voxel-wise, and IDPs of the various model outputs are extracted from a set of white matter tracts. Tensor fits utilize the b=1000 s/mm^2 data, producing maps including fractional anisotropy, tensor mode and mean diffusivity. The NODDI[23] model is fit using the AMICO (Accelerated Microstructure Imaging via Convex Optimization) tool[65], with outputs including intra-cellular volume fraction (which is often interpreted to reflect neurite density) and orientation dispersion (a measure of within-voxel disorganization). For tractography, a parametric approach is first used to estimate fibre orientations. The generalised ball & stick model is fit to the multi-shell data, estimating up to 3 crossing fibre orientations per voxel.[24, 82] Tractography is then performed in a probabilistic manner to estimate white matter pathways using the voxel-wise orientations.

Cross-subject alignment of white matter pathways is critical for extracting meaningful IDPs; here, two complementary approaches are used. The first used tract-based spatial statistics (TBSS[25, 28]), in which a standard-space white matter skeleton is mapped to each subject using a high-dimensional warp, after which ROIs are defined as the intersection of the skeleton with standard-space masks for 48 tracts[83] (see the "JHU ICBM-DTI-81 white-matter labels atlas" described at fsl.fmrib.ox.ac.uk/fsl/fslwiki/Atlases for definitions of the

tract regions and names). The second approach utilizes subject-specific probabilistic diffusion tractography run from both shells and using standard-space seeds to identify 27 tracts[25]; in this case, the output IDPs are weighted by the tractography output to emphasize values in regions that can most confidently be attributed to the tract of interest. Currently, no structural connectivity estimates from the diffusion tractography are provided as IDPs, but the probabilistic maps are available and future work will generate measures similar to those provided for resting-state fMRI.

Functional MRI

Task and resting-state fMRI use the same acquisition parameters, with 2.4mm spatial resolution and TR=0.735s, with multiband acceleration factor of 8. A "single-band" reference image (without the multiband excitation, exciting each slice independently) is acquired that has higher tissue-type image contrast; this is used as the target for motion correction and alignment. For both data sets, the raw data are corrected for motion[84] and distortion[68] and high-pass filtered to remove temporal drift.

The task scan used the Hariri faces/shapes "emotion" task[31, 85], as implemented in the HCP[22,], but with shorter overall duration and hence fewer total stimulus block repeats. The participants are presented with blocks of face or shape trials and asked to decide either which of two faces (or shapes) presented on the bottom of the screen match the face (or shape) at the top of the screen. The faces have either angry or fearful expressions. The ePrime stimulus script is available for download (http://biobank.ctsu.ox.ac.uk/crystal/refer.cgi?id=1462). Task-induced activation is modeled with FEAT, including auto-correlation correction[86], using 5 activation contrasts. Of these, the three contrasts of most interest (shapes, faces and faces>shapes) are used to generate output measures, including two IDPs for the faces-shapes task (one including all voxels above a group-level fixed-effects Z>120, and one including only the amygdala regions above threshold). IDPs corresponding to both percent signal change and statistical significance (Z statistics) are generated.

During resting-state scans, subjects are instructed to keep their eyes fixated on a crosshair, relax and "think of nothing in particular". Resting-state are identified using ICA (independent component analysis[43, 87]), which identifies components within the data that are spatially independent (where a component comprises a spatial map and a single associated time course). Following the pre-processing described above, resting-state fMRI data for each subject is further "cleaned" using an ICA-based algorithm for automatically identifying and removing structured artefacts[88]. This data is fed into group-level ICA (including an initial group-level dimensionality reduction[89]), which is used to parcellate the data set into sets of 25 and (separately) 100 spatially-independent components. Where a small (<30) number of components is estimated[90], it is common to consider each component as a separate "network" in its own right; each component will often include several non-contiguous regions, all having the same timecourse (according to the model). If a higher number of components is estimated[91], these are more likely to be smaller regions (parcels), which can then be considered as nodes for use in network analysis[92], where the spatial maps are used to define subject-specific time courses (the first stage of dual regression[1]). These time courses are used to estimate the size of signal fluctuation in each node, as well as to estimate connectivity between pairs of nodes using L2-regularised partial correlation[93]. The connectivity estimates are provided as IDPs at both parcellation dimensionalities (25 and 100 nodes); after removal of group-ICA components considered to be artefactual (i.e., relating either to scanning artefacts, or to non-neuronal biophysical processes such as cardiac fluctuations and head motion), this results in 21 and (respectively) 55 nodes left for forming the IDPs such as network matrices (functional connectivities between pairs of nodes).

Quality control

To date, raw data and pipeline outputs have been manually checked for gross problems of quality and robustness, with problematic data tagged and removed from pipeline outputs; see main text for results on proportions of usable data in the different modalities. However several quality-related IDPs are automatically generated by the pipeline (for example, number of outlier slices in the dMRI data, and measures of signal-to-noise ratio in the various modalities), and these can be used to help automatically identify problematic data. An expanded set of such quality measures is being produced, in addition to an automated machine learning system for flagging problematic data on the basis of the many IDPs and quality measures; future versions of the pipeline and data releases will benefit from the results of these ongoing developments.

Simple associations between brain IDPs and other measures in UK Biobank

We report simple correlation analyses between each of the 2501 brain IDPs and each of 1100 other variables extracted from the UK Biobank database (these other variables are mostly not derived from imaging, though some do come from the non-brain imaging modalities); for the list of general classes of these variables, see **Fig. 6a**, and for many examples of individual variables, see the lists associated with the CCA-ICA modes presented in **Fig. 7** and **Supplemental Figs**. The initial set of variables extracted from the UK Biobank database was automatically reduced to those (1100 variables) containing sufficient numbers of valid (non-missing) data entries, using very similar selection rules to those applied in the recent CCA-based analysis of Human Connectome Project data[44]. Some variables are defined (in the UK Biobank database) such that the numerical encoding is the inverse of what one might naturally assume - for example in the variable "Qualifications", higher numbers refer to lower levels of educational qualifications. In such cases we have inverted the sign of the ICA weightings printed in the figures, for ease of interpretation. Further, some variables are categorical, with no clear quantitative meaning to the values (e.g., "Transport type to work"); where we find an apparent association, this can be considered to be indicative of a real association (one might think of the analysis therefore as an over-conservative poor implementation of an ANOVA), but interpretation of the sign of the association clearly needs care. The analysis used data from the first 5430 subjects scanned and having usable imaging data: age range 44-78y (IQR 56-68y); 53% of subjects were female.

Eight confound variables are generated: age, age^2, sex, age×sex, age^2×sex, average head motion during tfMRI, average head motion during rfMRI and head size. To enforce Gaussianity, all confound variables, IDPs and non-IDP variables are first passed through a rank-based inverse Gaussian transformation; this improves the robustness of correlations (for example, to avoid undue influence of potential outlier values). The confounds are then regressed out of all IDPs and non-IDP variables to reduce the risk of finding non-meaningful associations. For example, head motion corrupts imaging data in complex ways[34], and also correlates with some diseases and with aging (r=0.15 in this data); hence, if not adjusted for, uninteresting associations would likely arise. However, some measures may have both biologically interesting associations with IDPs, as well as acting as an imaging confound. For example, abnormal heart rate or blood pressure could alter the fMRI signal through disrupted cerebral auto-regulation (independent of any changes to neural activity)[41], but cardiovascular pathology could also be related to neurological pathology. Similarly, overall brain size and gray matter thickness IDPs are sensitive simple markers of aging and disease; however, these properties can also affect other IDPs by changing the mixture of tissue types in an imaging voxel, creating an apparent age/disease dependence that is driven by the volume of tissue rather than the properties of a given tissue type (such as fMRI activation or white matter microstructural properties). It is therefore important to interpret apparent associations carefully.

The full set of 2.8million (2501×1100) correlations is then estimated and corrected for multiple comparisons. Bonferroni correction, which is likely to be somewhat conservative in such situations, due to non-independence across variables tested, resulted in $p_{corrected}<0.05$ being equivalent to requiring $p_{uncorrected}<1.8\times10^{-8}$. An alternative popular approach for multiple comparison correction is false discovery rate (FDR);[94] we use the more conservative FDR option (making no assumption of variable dependencies[95]), resulting here in requiring $p_{uncorrected}<3.8\times10^{-5}$. These two threshold levels are shown with dotted lines in all Manhattan plots in the figures.

Multivariate associations between brain IDPs and other measures: dominant modes of population variation

In the example multivariate analyses shown in **Figs 7-8**, canonical correlation analysis (CCA[42]) combined with independent component analysis (ICA[43]) is used to identify several "modes" of population covariation which link multiple brain IDPs to sets of other Biobank variables. This is following very similar to the methodology used recently to identify a single mode of population covariation between imaging measures and many behavioral and lifestyle measures in data from 461 subjects in the Human Connectome Project[15, 44].

IDP and non-IDP variables are prepared as for the univariate correlation analyses described above, resulting in a brain-IDP matrix of size 5034×2501 (subjects × IDPs) and a non-IDP matrix of size 5034×1100 (subjects × non-IDP variables). The intention is to feed these into CCA in order to identify population modes linking multiple variables from both matrices. However, in order to avoid an over-determined (rank deficient) CCA solution, we first compress both matrices along the respective phenotype dimension to 200 columns (i.e., much smaller than the numbers of subjects). This was done by separately reducing each matrix to the top 200 subject-eigenvectors using PCA. To achieve this while avoiding the problem of missing data, we use the approach detailed recently[44] of estimating first a pseudo-covariance matrix ignoring missing data, projecting this onto the nearest valid (positive definite) covariance matrix, and then carry out an eigenvalue decomposition. The two resulting (IDP and non-IDP) matrices of size 5034×200 are then fed into standard CCA ("canoncorr" in Matlab), resulting in 200 CCA modes being estimated. The CCA aims to identify symmetric linear relations between the two sets of variables.

Each significant CCA mode identifies a linear combination of IDPs and a linear combination of non-IDPs, where the variation in mode strength across subjects is maximally correlated. That is, CCA finds modes that relate sets of brain measures to sets of subjects' non-brain-imaging measures; for a graphical illustration of this approach, see Smith et al[44] (Supplemental information).

Permutation testing is then applied, to estimate (multiple-comparison-corrected) p-values for the CCA modes estimated. Nine modes are found to be significant ($p_{corrected}<0.002$, with all later modes having $p>0.05$). Because CCA can in general only unambiguously estimate distinct modes up to an orthogonal rotation amongst them (by direct analogy to PCA), we identify a non-ambiguous unmixing of the modes using ICA to optimize the final set of modes reported. Because we expect meaningful population modes to be much more structured (for example, sparser) in the cross-variable dimension than in the cross-subject dimension, we calculate ICA components that are statistically independent from each other in the cross-variable dimension. In order to take full advantage of the numbers of variables originally prepared, we first multiply the nine CCA subject-weight vectors into the original IDP and non-IDP data matrices (after concatenating these across variables), resulting in nine CCA variable-weight vectors of length 2501+1100=3601. These nine vectors are then fed into FastICA[43] in order to estimate nine population data sources having maximal statistical independence. This general approach (CCA, followed by concatenation of CCA weight vectors, followed by ICA) is similar to that proposed by Sui[96], except that we return to the full feature space (as described above) for the ICA stage, rather than staying in the PCA-reduced space. The ICA result is extremely robust, with split-half (cross-subject) reproducibility across the 9 ICA components of $r>0.89$. Interestingly, 5 of these ICA modes (including modes 7, 8 and 9, shown in **Fig. 7**) are virtually unchanged if the de-confounding step was omitted (correlation of variable-weights vectors: $r>0.8$).

Code and Results availability

As described above, all source data is available from UK Biobank via their standard data access procedure. The image processing and IDP pipeline will be made publicly available by FMRIB during 2016. The code for the univariate and multivariate tests described above, and the results of those tests (all univariate correlations and multivariate weight vectors) are available from *** *(location to be agreed by the journal – either at the journal website or at the FMRIB website – probably the latter is more straightforward)*. This online resource will be updated as more subjects' data and more IDPs become available.

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Supplementary Table 3 Full list of QC measures and IDPs.

QC measure	units	datattype	Description
QC_T1-to-standard_linear_alignment_discrepancy	AU	float	Discrepancy between the T1 brain image (linearly-aligned to standard space) and the standard-space brain template
QC_T1-to-standard_nonlinear_alignment_discrepancy	AU	float	Discrepancy between the T1 brain image (nonlinearly-aligned to standard space) and the standard-space brain template
QC_T1-to-standard_nonlinear_alignment_warping	AU	float	Amount of warping (averaged distortion) applied to nonlinearly align the T1 brain image to standard space
QC_T1_inverse_SNR ratio float	Inverted signal-to-noise ratio in the T1 - within-tissue spatial standard deviation divided by mean brain intensity		
QC_T1_inverse_CNR ratio float	Inverted contrast-to-noise ratio in the T1 - within-tissue spatial standard deviation divided by contrast between white and grey matter mean intensities		
QC_T2_FLAIR-to-T1_linear_alignment_discrepancy	AU	float	Discrepancy between the T2_FLAIR brain image (linearly-aligned to the T1) and the T1 brain image
QC_dMRI-to-T1_linear_alignment_discrepancy	AU	float	Discrepancy between the (EPI-unwarped b=0) dMRI brain image (linearly-aligned to the T1) and the T1 brain image
QC_SWI-to-T1_linear_alignment_discrepancy	AU	float	Discrepancy between the (magnitude) SWI brain image (linearly-aligned to the T1) and the T1 brain image
QC_rfMRI-to-T1_linear_alignment_discrepancy	AU	float	Discrepancy between the (EPI-unwarped SBref) rfMRI brain image (linearly-aligned to the T1) and the T1 brain image
QC_tfMRI-to-T1_linear_alignment_discrepancy	AU	float	Discrepancy between the (EPI-unwarped SBref) tfMRI brain image (linearly-aligned to the T1) and the T1 brain image
QC_rfMRI_head_motion mm float	Mean rfMRI head motion, averaged across space and timepoints		
QC_tfMRI_head_motion mm float	Mean tfMRI head motion, averaged across space and timepoints		
QC_rfMRI_inverse_tSNR ratio float	Inverted temporal signal-to-noise ratio in the pre-processed rfMRI - reciprocal of median (across brain voxels) of voxelwise mean intensity divided by voxelwise timeseries standard deviation		
QC_rfMRI_cleaned_inverse_tSNR ratio float	Inverted temporal signal-to-noise ratio in the artefact-cleaned pre-processed rfMRI - reciprocal of median (across brain voxels) of voxelwise mean intensity divided by voxelwise timeseries standard deviation		
QC_tfMRI_inverse_tSNR ratio float	Inverted temporal signal-to-noise ratio in the pre-processed tfMRI - reciprocal of median (across brain voxels) of voxelwise mean intensity divided by voxelwise timeseries standard deviation		
QC_dMRI_eddy_outlier_slices count int	Number of dMRI outlier slices (across all slices in all volumes) detected and corrected		
IDP_T1_SIENAX_headsize_scaling ratio float	Volumetric scaling from the T1 head image to standard space		

IDP name	units	datattype	Description
IDP_T1_SIENAX_peripheral_grey_normalised_volume	mm3	float	Volume of peripheral cortical grey matter (from T1 brain image, normalised for head size)
IDP_T1_SIENAX_peripheral_grey_unnormalised_volume	mm3	float	Volume of peripheral cortical grey matter (from T1 brain image)
IDP_T1_SIENAX_CSF_normalised_volume	mm3	float	Volume of ventricular cerebrospinal fluid (from T1 brain image, normalised for head size)
IDP_T1_SIENAX_CSF_unnormalised_volume	mm3	float	Volume of ventricular cerebrospinal fluid (from T1 brain image)
IDP_T1_SIENAX_grey_normalised_volume	mm3	float	Volume of grey matter (from T1 brain image, normalised for head size)
IDP_T1_SIENAX_grey_unnormalised_volume	mm3	float	Volume of grey matter (from T1 brain image)
IDP_T1_SIENAX_white_normalised_volume	mm3	float	Volume of white matter (from T1 brain image, normalised for head size)
IDP_T1_SIENAX_white_unnormalised_volume	mm3	float	Volume of white matter (from T1 brain image)
IDP_T1_SIENAX_brain-normalised_volume	mm3	float	Volume of brain (grey+white, from T1 brain image, normalised for head size)
IDP_T1_SIENAX_brain-unnormalised_volume	mm3	float	Volume of brain (grey+white, from T1 brain image)
IDP_T1_FIRST_left_thalamus_volume mm3	float	Volume of left thalamus (from T1 brain image)	
IDP_T1_FIRST_right_thalamus_volume mm3	float	Volume of right thalamus (from T1 brain image)	
IDP_T1_FIRST_left_caudate_volume mm3	float	Volume of left caudate (from T1 brain image)	
IDP_T1_FIRST_right_caudate_volume mm3	float	Volume of right caudate (from T1 brain image)	
IDP_T1_FIRST_left_putamen_volume mm3	float	Volume of left putamen (from T1 brain image)	
IDP_T1_FIRST_right_putamen_volume mm3	float	Volume of right putamen (from T1 brain image)	
IDP_T1_FIRST_left_pallidum_volume mm3	float	Volume of left pallidum (from T1 brain image)	
IDP_T1_FIRST_right_pallidum_volume mm3	float	Volume of right pallidum (from T1 brain image)	
IDP_T1_FIRST_left_hippocampus_volume	mm3	float	Volume of left hippocampus (from T1 brain image)
IDP_T1_FIRST_right_hippocampus_volume	mm3	float	Volume of right hippocampus (from T1 brain image)
IDP_T1_FIRST_left_amygdala_volume mm3	float	Volume of left amygdala (from T1 brain image)	
IDP_T1_FIRST_right_amygdala_volume mm3	float	Volume of right amygdala (from T1 brain image)	
IDP_T1_FIRST_left_accumbens_volume mm3	float	Volume of left accumbens (from T1 brain image)	
IDP_T1_FIRST_right_accumbens_volume mm3	float	Volume of right accumbens (from T1 brain image)	
IDP_T1_FIRST_brain_stem+4th_ventricle_volume	mm3	float	Volume of brain stem + 4th ventricle (from T1 brain image)
IDP_SWI_T2star_left_thalamus ms	float	Median T2star in left thalamus (from SWI data)	
IDP_SWI_T2star_right_thalamus ms	float	Median T2star in right thalamus (from SWI data)	
IDP_SWI_T2star_left_caudate ms	float	Median T2star in left caudate (from SWI data)	
IDP_SWI_T2star_right_caudate ms	float	Median T2star in right caudate (from SWI data)	
IDP_SWI_T2star_left_putamen ms	float	Median T2star in left putamen (from SWI data)	
IDP_SWI_T2star_right_putamen ms	float	Median T2star in right putamen (from SWI data)	
IDP_SWI_T2star_left_pallidum ms	float	Median T2star in left pallidum (from SWI data)	
IDP_SWI_T2star_right_pallidum ms	float	Median T2star in right pallidum (from SWI data)	
IDP_SWI_T2star_left_hippocampus ms	float	Median T2star in left hippocampus (from SWI data)	
IDP_SWI_T2star_right_hippocampus ms	float	Median T2star in right hippocampus (from SWI data)	
IDP_SWI_T2star_left_amygdala ms	float	Median T2star in left amygdala (from SWI data)	
IDP_SWI_T2star_right_amygdala ms	float	Median T2star in right amygdala (from SWI data)	
IDP_SWI_T2star_left_accumbens ms	float	Median T2star in left accumbens (from SWI data)	
IDP_SWI_T2star_right_accumbens ms	float	Median T2star in right accumbens (from SWI data)	
IDP_tfMRI_median_BOLD_shapes %	float	Median BOLD effect (in group-defined mask) for shapes activation (in task fMRI data)	
IDP_tfMRI_90th-percentile_BOLD_shapes	%	float	90th percentile of the BOLD effect (in group-defined mask) for shapes activation (in task fMRI data)
IDP_tfMRI_median_zstat_shapes Z	float	Median z-statistic (in group-defined mask) for shapes activation (in task fMRI data)	
IDP_tfMRI_90th-percentile_zstat_shapes	Z	float	90th percentile of the z-statistic (in group-defined mask) for shapes activation (in task fMRI data)
IDP_tfMRI_median_BOLD_faces %	float	Median BOLD effect (in group-defined mask) for faces activation (in task fMRI data)	
IDP_tfMRI_90th-percentile_BOLD_faces	%	float	90th percentile of the BOLD effect (in group-defined mask) for faces activation (in task fMRI data)
IDP_tfMRI_median_zstat_faces Z	float	Median z-statistic (in group-defined mask) for faces activation (in task fMRI data)	
IDP_tfMRI_90th-percentile_zstat_faces	Z	float	90th percentile of the z-statistic (in group-defined mask) for faces activation (in task fMRI data)
IDP_tfMRI_median_BOLD_faces-shapes %	float	Median BOLD effect (in group-defined mask) for shapes-faces contrast (in task fMRI data)	
IDP_tfMRI_90th-percentile_BOLD_faces-shapes	%	float	90th percentile of the BOLD effect (in group-defined mask) for shapes-faces contrast (in task fMRI data)
IDP_tfMRI_median_zstat_faces-shapes Z	float	Median z-statistic (in group-defined mask) for shapes-faces contrast (in task fMRI data)	
IDP_tfMRI_90th-percentile_zstat_faces-shapes	Z	float	90th percentile of the z-statistic (in group-defined mask) for shapes-faces contrast (in task fMRI data)
IDP_tfMRI_median_BOLD_faces-shapes_amygdala	%	float	Median BOLD effect (in group-defined amygdala activation mask) for shapes-faces contrast (in task fMRI data)
IDP_tfMRI_90th-percentile_BOLD_faces-shapes_amygdala	%	float	90th percentile of the BOLD effect (in group-defined amygdala activation mask) for shapes-faces contrast (in task fMRI data)
IDP_tfMRI_median_zstat_faces-shapes_amygdala	Z	float	Median z-statistic (in group-defined amygdala activation mask) for shapes-faces contrast (in task fMRI data)
IDP_tfMRI_90th-percentile_zstat_faces-shapes_amygdala	Z	float	90th percentile of the z-statistic (in group-defined amygdala activation mask) for shapes-faces contrast (in task fMRI data)
IDP_dMRI_TBSS_FA_Middle_cerebellar_peduncle	AU	float	Mean FA in middle cerebellar peduncle on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Pontine_crossing_tract	AU	float	Mean FA in pontine crossing tract on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Genu_of_corpus_callosum	AU	float	Mean FA in genu of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Body_of_corpus_callosum	AU	float	Mean FA in body of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Splenium_of_corpus_callosum	AU	float	Mean FA in splenium of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Fornix AU float	Mean FA in fornix on FA skeleton (from dMRI data)		
IDP_dMRI_TBSS_FA_Corticospinal_tract_R	AU	float	Mean FA in corticospinal tract (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Corticospinal_tract_L	AU	float	Mean FA in corticospinal tract (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Medial_lemniscus_R AU	float	Mean FA in medial lemniscus (right) on FA skeleton (from dMRI data)	
IDP_dMRI_TBSS_FA_Medial_lemniscus_L AU	float	Mean FA in medial lemniscus (left) on FA skeleton (from dMRI data)	
IDP_dMRI_TBSS_FA_Inferior_cerebellar_peduncle_R	AU	float	Mean FA in inferior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Inferior_cerebellar_peduncle_L	AU	float	Mean FA in inferior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Superior_cerebellar_peduncle_R	AU	float	Mean FA in superior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Superior_cerebellar_peduncle_L	AU	float	Mean FA in superior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Cerebral_peduncle_R	AU	float	Mean FA in cerebral peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Cerebral_peduncle_L	AU	float	Mean FA in cerebral peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Anterior_limb_of_internal_capsule_R	AU	float	Mean FA in anterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Anterior_limb_of_internal_capsule_L	AU	float	Mean FA in anterior limb of internal capsule (left) on FA skeleton (from dMRI data)

IDP_dMRI_TBSS_FA_Posterior_limb_of_internal_capsule_R AU float Mean FA in posterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Posterior_limb_of_internal_capsule_L AU float Mean FA in posterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Retrolenticular_part_of_internal_capsule_R AU float Mean FA in retrolenticular part of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Retrolenticular_part_of_internal_capsule_L AU float Mean FA in retrolenticular part of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Anterior_corona_radiata_R AU float Mean FA in anterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Anterior_corona_radiata_L AU float Mean FA in anterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Superior_corona_radiata_R AU float Mean FA in superior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Superior_corona_radiata_L AU float Mean FA in superior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Posterior_corona_radiata_R AU float Mean FA in posterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Posterior_corona_radiata_L AU float Mean FA in posterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Posterior_thalamic_radiation_R AU float Mean FA in posterior thalamic radiation (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Posterior_thalamic_radiation_L AU float Mean FA in posterior thalamic radiation (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Sagittal_stratum_R AU float Mean FA in sagittal stratum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Sagittal_stratum_L AU float Mean FA in sagittal stratum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_External_capsule_R AU float Mean FA in external capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_External_capsule_L AU float Mean FA in external capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Cingulum_cingulate_gyrus_R AU float Mean FA in cingulum cingulate gyrus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Cingulum_cingulate_gyrus_L AU float Mean FA in cingulum cingulate gyrus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Cingulum_hippocampus_R AU float Mean FA in cingulum hippocampus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Cingulum_hippocampus_L AU float Mean FA in cingulum hippocampus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Fornix_cres+Stria_terminalis_R AU float Mean FA in fornix cres+stria terminalis (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Fornix_cres+Stria_terminalis_L AU float Mean FA in fornix cres+stria terminalis (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Superior_longitudinal_fasciculus_R AU float Mean FA in superior longitudinal fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Superior_longitudinal_fasciculus_L AU float Mean FA in superior longitudinal fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Superior_fronto-occipital_fasciculus_R AU float Mean FA in superior fronto-occipital fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Superior_fronto-occipital_fasciculus_L AU float Mean FA in superior fronto-occipital fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Uncinate_fasciculus_R AU float Mean FA in uncinate fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Uncinate_fasciculus_L AU float Mean FA in uncinate fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Tapetum_R AU float Mean FA in tapetum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_FA_Tapetum_L AU float Mean FA in tapetum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Middle_cerebellar_peduncle AU float Mean MD in middle cerebellar peduncle on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Pontine_crossing_tract AU float Mean MD in pontine crossing tract on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Genu_of_corpus_callosum AU float Mean MD in genu of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Body_of_corpus_callosum AU float Mean MD in body of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Splenium_of_corpus_callosum AU float Mean MD in splenium of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Fornix AU float Mean MD in fornix on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Corticospinal_tract_R AU float Mean MD in corticospinal tract (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Corticospinal_tract_L AU float Mean MD in corticospinal tract (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Medial_lemniscus_R AU float Mean MD in medial lemniscus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Medial_lemniscus_L AU float Mean MD in medial lemniscus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Inferior_cerebellar_peduncle_R AU float Mean MD in inferior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Inferior_cerebellar_peduncle_L AU float Mean MD in inferior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Superior_cerebellar_peduncle_R AU float Mean MD in superior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Superior_cerebellar_peduncle_L AU float Mean MD in superior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Cerebral_peduncle_R AU float Mean MD in cerebral peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Cerebral_peduncle_L AU float Mean MD in cerebral peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Anterior_limb_of_internal_capsule_R AU float Mean MD in anterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Anterior_limb_of_internal_capsule_L AU float Mean MD in anterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Posterior_limb_of_internal_capsule_R AU float Mean MD in posterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Posterior_limb_of_internal_capsule_L AU float Mean MD in posterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Retrolenticular_part_of_internal_capsule_R AU float Mean MD in retrolenticular part of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Retrolenticular_part_of_internal_capsule_L AU float Mean MD in retrolenticular part of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Anterior_corona_radiata_R AU float Mean MD in anterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Anterior_corona_radiata_L AU float Mean MD in anterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Superior_corona_radiata_R AU float Mean MD in superior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Superior_corona_radiata_L AU float Mean MD in superior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Posterior_corona_radiata_R AU float Mean MD in posterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Posterior_corona_radiata_L AU float Mean MD in posterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Posterior_thalamic_radiation_R AU float Mean MD in posterior thalamic radiation (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Posterior_thalamic_radiation_L AU float Mean MD in posterior thalamic radiation (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Sagittal_stratum_R AU float Mean MD in sagittal stratum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Sagittal_stratum_L AU float Mean MD in sagittal stratum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_External_capsule_R AU float Mean MD in external capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_External_capsule_L AU float Mean MD in external capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Cingulum_cingulate_gyrus_R AU float Mean MD in cingulum cingulate gyrus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Cingulum_cingulate_gyrus_L AU float Mean MD in cingulum cingulate gyrus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Cingulum_hippocampus_R AU float Mean MD in cingulum hippocampus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Cingulum_hippocampus_L AU float Mean MD in cingulum hippocampus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Fornix_cres+Stria_terminalis_R AU float Mean MD in fornix cres+stria terminalis (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Fornix_cres+Stria_terminalis_L AU float Mean MD in fornix cres+stria terminalis (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Superior_longitudinal_fasciculus_R AU float Mean MD in superior longitudinal fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Superior_longitudinal_fasciculus_L AU float Mean MD in superior longitudinal fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Superior_fronto-occipital_fasciculus_R AU float Mean MD in superior fronto-occipital fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Superior_fronto-occipital_fasciculus_L AU float Mean MD in superior fronto-occipital fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Uncinate_fasciculus_R AU float Mean MD in uncinate fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Uncinate_fasciculus_L AU float Mean MD in uncinate fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Tapetum_R AU float Mean MD in tapetum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MD_Tapetum_L AU float Mean MD in tapetum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Middle_cerebellar_peduncle AU float Mean MO in middle cerebellar peduncle on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Pontine_crossing_tract AU float Mean MO in pontine crossing tract on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Genu_of_corpus_callosum AU float Mean MO in genu of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Body_of_corpus_callosum AU float Mean MO in body of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Splenium_of_corpus_callosum AU float Mean MO in splenium of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Fornix AU float Mean MO in fornix on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Corticospinal_tract_R AU float Mean MO in corticospinal tract (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Corticospinal_tract_L AU float Mean MO in corticospinal tract (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Medial_lemniscus_R AU float Mean MO in medial lemniscus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Medial_lemniscus_L AU float Mean MO in medial lemniscus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Inferior_cerebellar_peduncle_R AU float Mean MO in inferior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Inferior_cerebellar_peduncle_L AU float Mean MO in inferior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Superior_cerebellar_peduncle_R AU float Mean MO in superior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Superior_cerebellar_peduncle_L AU float Mean MO in superior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Cerebral_peduncle_R AU float Mean MO in cerebral peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Cerebral_peduncle_L AU float Mean MO in cerebral peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Anterior_limb_of_internal_capsule_R AU float Mean MO in anterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Anterior_limb_of_internal_capsule_L AU float Mean MO in anterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Posterior_limb_of_internal_capsule_R AU float Mean MO in posterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Posterior_limb_of_internal_capsule_L AU float Mean MO in posterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Retrolenticular_part_of_internal_capsule_R AU float Mean MO in retrolenticular part of internal capsule (right) on FA skeleton (from dMRI data)

IDP_dMRI_TBSS_MO_Retrolenticular_part_of_internal_capsule_L AU float Mean MO in retrolenticular part of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Anterior_corona_radiata_R AU float Mean MO in anterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Anterior_corona_radiata_L AU float Mean MO in anterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Superior_corona_radiata_R AU float Mean MO in superior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Superior_corona_radiata_L AU float Mean MO in superior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Posterior_corona_radiata_R AU float Mean MO in posterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Posterior_corona_radiata_L AU float Mean MO in posterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Posterior_thalamic_radiation_R AU float Mean MO in posterior thalamic radiation (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Posterior_thalamic_radiation_L AU float Mean MO in posterior thalamic radiation (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Sagittal_stratum_R AU float Mean MO in sagittal stratum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Sagittal_stratum_L AU float Mean MO in sagittal stratum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_External_capsule_R AU float Mean MO in external capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_External_capsule_L AU float Mean MO in external capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Cingulum_cingulate_gyrus_R AU float Mean MO in cingulum cingulate gyrus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Cingulum_cingulate_gyrus_L AU float Mean MO in cingulum cingulate gyrus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Cingulum_hippocampus_R AU float Mean MO in cingulum hippocampus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Cingulum_hippocampus_L AU float Mean MO in cingulum hippocampus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Fornix_cres+Stria_terminalis_R AU float Mean MO in fornix cres+stria terminalis (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Fornix_cres+Stria_terminalis_L AU float Mean MO in fornix cres+stria terminalis (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Superior_longitudinal_fasciculus_R AU float Mean MO in superior longitudinal fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Superior_longitudinal_fasciculus_L AU float Mean MO in superior longitudinal fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Superior_fronto-occipital_fasciculus_R AU float Mean MO in superior fronto-occipital fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Superior_fronto-occipital_fasciculus_L AU float Mean MO in superior fronto-occipital fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Uncinate_fasciculus_R AU float Mean MO in uncinate fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Uncinate_fasciculus_L AU float Mean MO in uncinate fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Tapetum_R AU float Mean MO in tapetum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_MO_Tapetum_L AU float Mean MO in tapetum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Middle_cerebellar_peduncle AU float Mean L1 in middle cerebellar peduncle on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Pontine_crossing_tract AU float Mean L1 in pontine crossing tract on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Genu_of_corpus_callosum AU float Mean L1 in genu of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Body_of_corpus_callosum AU float Mean L1 in body of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Splenium_of_corpus_callosum AU float Mean L1 in splenium of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Fornix AU float Mean L1 in fornix on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Corticospinal_tract_R AU float Mean L1 in corticospinal tract (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Corticospinal_tract_L AU float Mean L1 in corticospinal tract (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Medial_lemniscus_R AU float Mean L1 in medial lemniscus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Medial_lemniscus_L AU float Mean L1 in medial lemniscus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Inferior_cerebellar_peduncle_R AU float Mean L1 in inferior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Inferior_cerebellar_peduncle_L AU float Mean L1 in inferior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Superior_cerebellar_peduncle_R AU float Mean L1 in superior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Superior_cerebellar_peduncle_L AU float Mean L1 in superior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Cerebral_peduncle_R AU float Mean L1 in cerebral peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Cerebral_peduncle_L AU float Mean L1 in cerebral peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Anterior_limb_of_internal_capsule_R AU float Mean L1 in anterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Anterior_limb_of_internal_capsule_L AU float Mean L1 in anterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Posterior_limb_of_internal_capsule_R AU float Mean L1 in posterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Posterior_limb_of_internal_capsule_L AU float Mean L1 in posterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Retrolenticular_part_of_internal_capsule_R AU float Mean L1 in retrolenticular part of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Retrolenticular_part_of_internal_capsule_L AU float Mean L1 in retrolenticular part of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Anterior_corona_radiata_R AU float Mean L1 in anterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Anterior_corona_radiata_L AU float Mean L1 in anterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Superior_corona_radiata_R AU float Mean L1 in superior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Superior_corona_radiata_L AU float Mean L1 in superior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Posterior_corona_radiata_R AU float Mean L1 in posterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Posterior_corona_radiata_L AU float Mean L1 in posterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Posterior_thalamic_radiation_R AU float Mean L1 in posterior thalamic radiation (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Posterior_thalamic_radiation_L AU float Mean L1 in posterior thalamic radiation (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Sagittal_stratum_R AU float Mean L1 in sagittal stratum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Sagittal_stratum_L AU float Mean L1 in sagittal stratum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_External_capsule_R AU float Mean L1 in external capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_External_capsule_L AU float Mean L1 in external capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Cingulum_cingulate_gyrus_R AU float Mean L1 in cingulum cingulate gyrus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Cingulum_cingulate_gyrus_L AU float Mean L1 in cingulum cingulate gyrus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Cingulum_hippocampus_R AU float Mean L1 in cingulum hippocampus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Cingulum_hippocampus_L AU float Mean L1 in cingulum hippocampus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Fornix_cres+Stria_terminalis_R AU float Mean L1 in fornix cres+stria terminalis (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Fornix_cres+Stria_terminalis_L AU float Mean L1 in fornix cres+stria terminalis (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Superior_longitudinal_fasciculus_R AU float Mean L1 in superior longitudinal fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Superior_longitudinal_fasciculus_L AU float Mean L1 in superior longitudinal fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Superior_fronto-occipital_fasciculus_R AU float Mean L1 in superior fronto-occipital fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Superior_fronto-occipital_fasciculus_L AU float Mean L1 in superior fronto-occipital fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Uncinate_fasciculus_R AU float Mean L1 in uncinate fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Uncinate_fasciculus_L AU float Mean L1 in uncinate fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Tapetum_R AU float Mean L1 in tapetum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L1_Tapetum_L AU float Mean L1 in tapetum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Middle_cerebellar_peduncle AU float Mean L2 in middle cerebellar peduncle on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Pontine_crossing_tract AU float Mean L2 in pontine crossing tract on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Genu_of_corpus_callosum AU float Mean L2 in genu of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Body_of_corpus_callosum AU float Mean L2 in body of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Splenium_of_corpus_callosum AU float Mean L2 in splenium of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Fornix AU float Mean L2 in fornix on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Corticospinal_tract_R AU float Mean L2 in corticospinal tract (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Corticospinal_tract_L AU float Mean L2 in corticospinal tract (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Medial_lemniscus_R AU float Mean L2 in medial lemniscus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Medial_lemniscus_L AU float Mean L2 in medial lemniscus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Inferior_cerebellar_peduncle_R AU float Mean L2 in inferior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Inferior_cerebellar_peduncle_L AU float Mean L2 in inferior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Superior_cerebellar_peduncle_R AU float Mean L2 in superior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Superior_cerebellar_peduncle_L AU float Mean L2 in superior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Cerebral_peduncle_R AU float Mean L2 in cerebral peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Cerebral_peduncle_L AU float Mean L2 in cerebral peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Anterior_limb_of_internal_capsule_R AU float Mean L2 in anterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Anterior_limb_of_internal_capsule_L AU float Mean L2 in anterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Posterior_limb_of_internal_capsule_R AU float Mean L2 in posterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Posterior_limb_of_internal_capsule_L AU float Mean L2 in posterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Retrolenticular_part_of_internal_capsule_R AU float Mean L2 in retrolenticular part of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Retrolenticular_part_of_internal_capsule_L AU float Mean L2 in retrolenticular part of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Anterior_corona_radiata_R AU float Mean L2 in anterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Anterior_corona_radiata_L AU float Mean L2 in anterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Superior_corona_radiata_R AU float Mean L2 in superior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Superior_corona_radiata_L AU float Mean L2 in superior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Posterior_corona_radiata_R AU float Mean L2 in posterior corona radiata (right) on FA skeleton (from dMRI data)

IDP_dMRI_TBSS_L2_Posterior_corona_radiata_L AU float Mean L2 in posterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Posterior_thalamic_radiation_R AU float Mean L2 in posterior thalamic radiation (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Posterior_thalamic_radiation_L AU float Mean L2 in posterior thalamic radiation (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Sagittal_stratum_R AU float Mean L2 in sagittal stratum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Sagittal_stratum_L AU float Mean L2 in sagittal stratum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_External_capsule_R AU float Mean L2 in external capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_External_capsule_L AU float Mean L2 in external capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Cingulum_cingulate_gyrus_R AU float Mean L2 in cingulum cingulate gyrus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Cingulum_cingulate_gyrus_L AU float Mean L2 in cingulum cingulate gyrus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Cingulum_hippocampus_R AU float Mean L2 in cingulum hippocampus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Cingulum_hippocampus_L AU float Mean L2 in cingulum hippocampus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Fornix_cres+Stria_terminalis_R AU float Mean L2 in fornix cres+stria terminalis (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Fornix_cres+Stria_terminalis_L AU float Mean L2 in fornix cres+stria terminalis (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Superior_longitudinal_fasciculus_R AU float Mean L2 in superior longitudinal fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Superior_longitudinal_fasciculus_L AU float Mean L2 in superior longitudinal fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Superior_fronto-occipital_fasciculus_R AU float Mean L2 in superior fronto-occipital fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Superior_fronto-occipital_fasciculus_L AU float Mean L2 in superior fronto-occipital fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Uncinate_fasciculus_R AU float Mean L2 in uncinate fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Uncinate_fasciculus_L AU float Mean L2 in uncinate fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Tapetum_R AU float Mean L2 in tapetum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L2_Tapetum_L AU float Mean L2 in tapetum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Middle_cerebellar_peduncle AU float Mean L3 in middle cerebellar peduncle on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Pontine_crossing_tract AU float Mean L3 in pontine crossing tract on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Genu_of_corpus_callosum AU float Mean L3 in genu of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Body_of_corpus_callosum AU float Mean L3 in body of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Splenium_of_corpus_callosum AU float Mean L3 in splenium of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Fornix AU float Mean L3 in fornix on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Corticospinal_tract_R AU float Mean L3 in corticospinal tract (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Corticospinal_tract_L AU float Mean L3 in corticospinal tract (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Medial_lemniscus_R AU float Mean L3 in medial lemniscus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Medial_lemniscus_L AU float Mean L3 in medial lemniscus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Inferior_cerebellar_peduncle_R AU float Mean L3 in inferior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Inferior_cerebellar_peduncle_L AU float Mean L3 in inferior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Superior_cerebellar_peduncle_R AU float Mean L3 in superior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Superior_cerebellar_peduncle_L AU float Mean L3 in superior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Cerebral_peduncle_R AU float Mean L3 in cerebral peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Cerebral_peduncle_L AU float Mean L3 in cerebral peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Anterior_limb_of_internal_capsule_R AU float Mean L3 in anterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Anterior_limb_of_internal_capsule_L AU float Mean L3 in anterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Posterior_limb_of_internal_capsule_R AU float Mean L3 in posterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Posterior_limb_of_internal_capsule_L AU float Mean L3 in posterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Retrolenticular_part_of_internal_capsule_R AU float Mean L3 in retrolenticular part of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Retrolenticular_part_of_internal_capsule_L AU float Mean L3 in retrolenticular part of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Anterior_corona_radiata_R AU float Mean L3 in anterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Anterior_corona_radiata_L AU float Mean L3 in anterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Superior_corona_radiata_R AU float Mean L3 in superior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Superior_corona_radiata_L AU float Mean L3 in superior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Posterior_corona_radiata_R AU float Mean L3 in posterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Posterior_corona_radiata_L AU float Mean L3 in posterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Posterior_thalamic_radiation_R AU float Mean L3 in posterior thalamic radiation (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Posterior_thalamic_radiation_L AU float Mean L3 in posterior thalamic radiation (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Sagittal_stratum_R AU float Mean L3 in sagittal stratum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Sagittal_stratum_L AU float Mean L3 in sagittal stratum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_External_capsule_R AU float Mean L3 in external capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_External_capsule_L AU float Mean L3 in external capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Cingulum_cingulate_gyrus_R AU float Mean L3 in cingulum cingulate gyrus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Cingulum_cingulate_gyrus_L AU float Mean L3 in cingulum cingulate gyrus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Cingulum_hippocampus_R AU float Mean L3 in cingulum hippocampus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Cingulum_hippocampus_L AU float Mean L3 in cingulum hippocampus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Fornix_cres+Stria_terminalis_R AU float Mean L3 in fornix cres+stria terminalis (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Fornix_cres+Stria_terminalis_L AU float Mean L3 in fornix cres+stria terminalis (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Superior_longitudinal_fasciculus_R AU float Mean L3 in superior longitudinal fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Superior_longitudinal_fasciculus_L AU float Mean L3 in superior longitudinal fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Superior_fronto-occipital_fasciculus_R AU float Mean L3 in superior fronto-occipital fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Superior_fronto-occipital_fasciculus_L AU float Mean L3 in superior fronto-occipital fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Uncinate_fasciculus_R AU float Mean L3 in uncinate fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Uncinate_fasciculus_L AU float Mean L3 in uncinate fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Tapetum_R AU float Mean L3 in tapetum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_L3_Tapetum_L AU float Mean L3 in tapetum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Middle_cerebellar_peduncle AU float Mean ICVF in middle cerebellar peduncle on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Pontine_crossing_tract AU float Mean ICVF in pontine crossing tract on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Genu_of_corpus_callosum AU float Mean ICVF in genu of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Body_of_corpus_callosum AU float Mean ICVF in body of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Splenium_of_corpus_callosum AU float Mean ICVF in splenium of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Fornix AU float Mean ICVF in fornix on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Corticospinal_tract_R AU float Mean ICVF in corticospinal tract (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Corticospinal_tract_L AU float Mean ICVF in corticospinal tract (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Medial_lemniscus_R AU float Mean ICVF in medial lemniscus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Medial_lemniscus_L AU float Mean ICVF in medial lemniscus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Inferior_cerebellar_peduncle_R AU float Mean ICVF in inferior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Inferior_cerebellar_peduncle_L AU float Mean ICVF in inferior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Superior_cerebellar_peduncle_R AU float Mean ICVF in superior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Superior_cerebellar_peduncle_L AU float Mean ICVF in superior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Cerebral_peduncle_R AU float Mean ICVF in cerebral peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Cerebral_peduncle_L AU float Mean ICVF in cerebral peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Anterior_limb_of_internal_capsule_R AU float Mean ICVF in anterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Anterior_limb_of_internal_capsule_L AU float Mean ICVF in anterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Posterior_limb_of_internal_capsule_R AU float Mean ICVF in posterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Posterior_limb_of_internal_capsule_L AU float Mean ICVF in posterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Retrolenticular_part_of_internal_capsule_R AU float Mean ICVF in retrolenticular part of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Retrolenticular_part_of_internal_capsule_L AU float Mean ICVF in retrolenticular part of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Anterior_corona_radiata_R AU float Mean ICVF in anterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Anterior_corona_radiata_L AU float Mean ICVF in anterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Superior_corona_radiata_R AU float Mean ICVF in superior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Superior_corona_radiata_L AU float Mean ICVF in superior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Posterior_corona_radiata_R AU float Mean ICVF in posterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Posterior_corona_radiata_L AU float Mean ICVF in posterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Posterior_thalamic_radiation_R AU float Mean ICVF in posterior thalamic radiation (right) on FA skeleton (from dMRI data)

IDP_dMRI_TBSS_ICVF_Posterior_thalamic_radiation_L AU float Mean ICVF in posterior thalamic radiation (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Sagittal_stratum_R AU float Mean ICVF in sagittal stratum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Sagittal_stratum_L AU float Mean ICVF in sagittal stratum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_External_capsule_R AU float Mean ICVF in external capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_External_capsule_L AU float Mean ICVF in external capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Cingulum_cingulate_gyrus_R AU float Mean ICVF in cingulum cingulate gyrus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Cingulum_cingulate_gyrus_L AU float Mean ICVF in cingulum cingulate gyrus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Cingulum_hippocampus_R AU float Mean ICVF in cingulum hippocampus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Cingulum_hippocampus_L AU float Mean ICVF in cingulum hippocampus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Fornix_cres+Stria_terminalis_R AU float Mean ICVF in fornix cres+stria terminalis (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Fornix_cres+Stria_terminalis_L AU float Mean ICVF in fornix cres+stria terminalis (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Superior_longitudinal_fasciculus_R AU float Mean ICVF in superior longitudinal fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Superior_longitudinal_fasciculus_L AU float Mean ICVF in superior longitudinal fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Superior_fronto-occipital_fasciculus_R AU float Mean ICVF in superior fronto-occipital fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Superior_fronto-occipital_fasciculus_L AU float Mean ICVF in superior fronto-occipital fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Uncinate_fasciculus_R AU float Mean ICVF in uncinate fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Uncinate_fasciculus_L AU float Mean ICVF in uncinate fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Tapetum_R AU float Mean ICVF in tapetum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ICVF_Tapetum_L AU float Mean ICVF in tapetum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Middle_cerebellar_peduncle AU float Mean OD in middle cerebellar peduncle on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Pontine_crossing_tract AU float Mean OD in pontine crossing tract on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Genu_of_corpus_callosum AU float Mean OD in genu of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Body_of_corpus_callosum AU float Mean OD in body of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Splenium_of_corpus_callosum AU float Mean OD in splenium of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Fornix AU float Mean OD in fornix on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Corticospinal_tract_R AU float Mean OD in corticospinal tract (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Corticospinal_tract_L AU float Mean OD in corticospinal tract (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Medial_lemniscus_R AU float Mean OD in medial lemniscus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Medial_lemniscus_L AU float Mean OD in medial lemniscus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Inferior_cerebellar_peduncle_R AU float Mean OD in inferior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Inferior_cerebellar_peduncle_L AU float Mean OD in inferior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Superior_cerebellar_peduncle_R AU float Mean OD in superior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Superior_cerebellar_peduncle_L AU float Mean OD in superior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Cerebral_peduncle_R AU float Mean OD in cerebral peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Cerebral_peduncle_L AU float Mean OD in cerebral peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Anterior_limb_of_internal_capsule_R AU float Mean OD in anterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Anterior_limb_of_internal_capsule_L AU float Mean OD in anterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Posterior_limb_of_internal_capsule_R AU float Mean OD in posterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Posterior_limb_of_internal_capsule_L AU float Mean OD in posterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Retrolenticular_part_of_internal_capsule_R AU float Mean OD in retrolenticular part of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Retrolenticular_part_of_internal_capsule_L AU float Mean OD in retrolenticular part of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Anterior_corona_radiata_R AU float Mean OD in anterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Anterior_corona_radiata_L AU float Mean OD in anterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Superior_corona_radiata_R AU float Mean OD in superior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Superior_corona_radiata_L AU float Mean OD in superior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Posterior_corona_radiata_R AU float Mean OD in posterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Posterior_corona_radiata_L AU float Mean OD in posterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Posterior_thalamic_radiation_R AU float Mean OD in posterior thalamic radiation (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Posterior_thalamic_radiation_L AU float Mean OD in posterior thalamic radiation (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Sagittal_stratum_R AU float Mean OD in sagittal stratum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Sagittal_stratum_L AU float Mean OD in sagittal stratum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_External_capsule_R AU float Mean OD in external capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_External_capsule_L AU float Mean OD in external capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Cingulum_cingulate_gyrus_R AU float Mean OD in cingulum cingulate gyrus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Cingulum_cingulate_gyrus_L AU float Mean OD in cingulum cingulate gyrus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Cingulum_hippocampus_R AU float Mean OD in cingulum hippocampus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Cingulum_hippocampus_L AU float Mean OD in cingulum hippocampus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Fornix_cres+Stria_terminalis_R AU float Mean OD in fornix cres+stria terminalis (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Fornix_cres+Stria_terminalis_L AU float Mean OD in fornix cres+stria terminalis (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Superior_longitudinal_fasciculus_R AU float Mean OD in superior longitudinal fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Superior_longitudinal_fasciculus_L AU float Mean OD in superior longitudinal fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Superior_fronto-occipital_fasciculus_R AU float Mean OD in superior fronto-occipital fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Superior_fronto-occipital_fasciculus_L AU float Mean OD in superior fronto-occipital fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Uncinate_fasciculus_R AU float Mean OD in uncinate fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Uncinate_fasciculus_L AU float Mean OD in uncinate fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Tapetum_R AU float Mean OD in tapetum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_OD_Tapetum_L AU float Mean OD in tapetum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Middle_cerebellar_peduncle AU float Mean ISOVF in middle cerebellar peduncle on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Pontine_crossing_tract AU float Mean ISOVF in pontine crossing tract on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Genu_of_corpus_callosum AU float Mean ISOVF in genu of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Body_of_corpus_callosum AU float Mean ISOVF in body of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Splenium_of_corpus_callosum AU float Mean ISOVF in splenium of corpus callosum on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Fornix AU float Mean ISOVF in fornix on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Corticospinal_tract_R AU float Mean ISOVF in corticospinal tract (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Corticospinal_tract_L AU float Mean ISOVF in corticospinal tract (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Medial_lemniscus_R AU float Mean ISOVF in medial lemniscus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Medial_lemniscus_L AU float Mean ISOVF in medial lemniscus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Inferior_cerebellar_peduncle_R AU float Mean ISOVF in inferior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Inferior_cerebellar_peduncle_L AU float Mean ISOVF in inferior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Superior_cerebellar_peduncle_R AU float Mean ISOVF in superior cerebellar peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Superior_cerebellar_peduncle_L AU float Mean ISOVF in superior cerebellar peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Cerebral_peduncle_R AU float Mean ISOVF in cerebral peduncle (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Cerebral_peduncle_L AU float Mean ISOVF in cerebral peduncle (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Anterior_limb_of_internal_capsule_R AU float Mean ISOVF in anterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Anterior_limb_of_internal_capsule_L AU float Mean ISOVF in anterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Posterior_limb_of_internal_capsule_R AU float Mean ISOVF in posterior limb of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Posterior_limb_of_internal_capsule_L AU float Mean ISOVF in posterior limb of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Retrolenticular_part_of_internal_capsule_R AU float Mean ISOVF in retrolenticular part of internal capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Retrolenticular_part_of_internal_capsule_L AU float Mean ISOVF in retrolenticular part of internal capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Anterior_corona_radiata_R AU float Mean ISOVF in anterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Anterior_corona_radiata_L AU float Mean ISOVF in anterior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Superior_corona_radiata_R AU float Mean ISOVF in superior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Superior_corona_radiata_L AU float Mean ISOVF in superior corona radiata (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Posterior_corona_radiata_R AU float Mean ISOVF in posterior corona radiata (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Posterior_corona_radiata_L AU float Mean ISOVF in posterior corona radiata (left) on FA skeleton (from dMRI data)

IDP_dMRI_TBSS_ISOVF_Posterior_thalamic_radiation_R	AU	float	Mean ISOVF in posterior thalamic radiation (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Posterior_thalamic_radiation_L	AU	float	Mean ISOVF in posterior thalamic radiation (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Sagittal_stratum_R	AU	float	Mean ISOVF in sagittal stratum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Sagittal_stratum_L	AU	float	Mean ISOVF in sagittal stratum (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_External_capsule_R	AU	float	Mean ISOVF in external capsule (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_External_capsule_L	AU	float	Mean ISOVF in external capsule (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Cingulum_cingulate_gyrus_R	AU	float	Mean ISOVF in cingulum cingulate gyrus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Cingulum_cingulate_gyrus_L	AU	float	Mean ISOVF in cingulum cingulate gyrus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Cingulum_hippocampus_R	AU	float	Mean ISOVF in cingulum hippocampus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Cingulum_hippocampus_L	AU	float	Mean ISOVF in cingulum hippocampus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Fornix_cres+Stria_terminalis_R	AU	float	Mean ISOVF in fornix cres+stria terminalis (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Fornix_cres+Stria_terminalis_L	AU	float	Mean ISOVF in fornix cres+stria terminalis (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Superior_longitudinal_fasciculus_R	AU	float	Mean ISOVF in superior longitudinal fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Superior_longitudinal_fasciculus_L	AU	float	Mean ISOVF in superior longitudinal fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Superior_fronto-occipital_fasciculus_R	AU	float	Mean ISOVF in superior fronto-occipital fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Superior_fronto-occipital_fasciculus_L	AU	float	Mean ISOVF in superior fronto-occipital fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Uncinate_fasciculus_R	AU	float	Mean ISOVF in uncinate fasciculus (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Uncinate_fasciculus_L	AU	float	Mean ISOVF in uncinate fasciculus (left) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Tapetum_R	AU	float	Mean ISOVF in tapetum (right) on FA skeleton (from dMRI data)
IDP_dMRI_TBSS_ISOVF_Tapetum_L	AU	float	Mean ISOVF in tapetum (left) on FA skeleton (from dMRI data)
IDP_dMRI_ProbtrackX_FA_ar_l	AU	float	Weighted-mean FA in tract left acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_FA_ar_r	AU	float	Weighted-mean FA in tract right acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_FA_atr_l	AU	float	Weighted-mean FA in tract left anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_FA_atr_r	AU	float	Weighted-mean FA in tract right anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_FA_cgc_l	AU	float	Weighted-mean FA in tract left cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_FA_cgc_r	AU	float	Weighted-mean FA in tract right cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_FA_cgh_l	AU	float	Weighted-mean FA in tract left parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_FA_cgh_r	AU	float	Weighted-mean FA in tract right parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_FA_cst_l	AU	float	Weighted-mean FA in tract left corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_FA_cst_r	AU	float	Weighted-mean FA in tract right corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_FA_fma	AU	float	Weighted-mean FA in tract forceps major (from dMRI data)
IDP_dMRI_ProbtrackX_FA_fmi	AU	float	Weighted-mean FA in tract forceps minor (from dMRI data)
IDP_dMRI_ProbtrackX_FA_ifo_l	AU	float	Weighted-mean FA in tract left inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_FA_ifo_r	AU	float	Weighted-mean FA in tract right inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_FA_ilf_l	AU	float	Weighted-mean FA in tract left inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_FA_ilf_r	AU	float	Weighted-mean FA in tract right inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_FA_mcp	AU	float	Weighted-mean FA in tract middle cerebellar peduncle (from dMRI data)
IDP_dMRI_ProbtrackX_FA_ml_l	AU	float	Weighted-mean FA in tract left medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_FA_ml_r	AU	float	Weighted-mean FA in tract right medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_FA_ptr_l	AU	float	Weighted-mean FA in tract left posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_FA_ptr_r	AU	float	Weighted-mean FA in tract right posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_FA_slf_l	AU	float	Weighted-mean FA in tract left superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_FA_slf_r	AU	float	Weighted-mean FA in tract rigt superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_FA_str_l	AU	float	Weighted-mean FA in tract left superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_FA_str_r	AU	float	Weighted-mean FA in tract right superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_FA_unc_l	AU	float	Weighted-mean FA in tract left uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_FA_unc_r	AU	float	Weighted-mean FA in tract right uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MD_ar_l	AU	float	Weighted-mean MD in tract left acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MD_ar_r	AU	float	Weighted-mean MD in tract right acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MD_atr_l	AU	float	Weighted-mean MD in tract left anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MD_atr_r	AU	float	Weighted-mean MD in tract right anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MD_cgc_l	AU	float	Weighted-mean MD in tract left cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_MD_cgc_r	AU	float	Weighted-mean MD in tract right cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_MD_cgh_l	AU	float	Weighted-mean MD in tract left parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_MD_cgh_r	AU	float	Weighted-mean MD in tract right parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_MD_cst_l	AU	float	Weighted-mean MD in tract left corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_MD_cst_r	AU	float	Weighted-mean MD in tract right corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_MD_fma	AU	float	Weighted-mean MD in tract forceps major (from dMRI data)
IDP_dMRI_ProbtrackX_MD_fmi	AU	float	Weighted-mean MD in tract forceps minor (from dMRI data)
IDP_dMRI_ProbtrackX_MD_ifo_l	AU	float	Weighted-mean MD in tract left inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MD_ifo_r	AU	float	Weighted-mean MD in tract right inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MD_ilf_l	AU	float	Weighted-mean MD in tract left inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MD_ilf_r	AU	float	Weighted-mean MD in tract right inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MD_mcp	AU	float	Weighted-mean MD in tract middle cerebellar peduncle (from dMRI data)
IDP_dMRI_ProbtrackX_MD_ml_l	AU	float	Weighted-mean MD in tract left medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_MD_ml_r	AU	float	Weighted-mean MD in tract right medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_MD_ptr_l	AU	float	Weighted-mean MD in tract left posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MD_ptr_r	AU	float	Weighted-mean MD in tract right posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MD_slf_l	AU	float	Weighted-mean MD in tract left superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MD_slf_r	AU	float	Weighted-mean MD in tract rigt superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MD_str_l	AU	float	Weighted-mean MD in tract left superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MD_str_r	AU	float	Weighted-mean MD in tract right superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MD_unc_l	AU	float	Weighted-mean MD in tract left uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MD_unc_r	AU	float	Weighted-mean MD in tract right uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MO_ar_l	AU	float	Weighted-mean MO in tract left acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MO_ar_r	AU	float	Weighted-mean MO in tract right acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MO_atr_l	AU	float	Weighted-mean MO in tract left anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MO_atr_r	AU	float	Weighted-mean MO in tract right anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MO_cgc_l	AU	float	Weighted-mean MO in tract left cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_MO_cgc_r	AU	float	Weighted-mean MO in tract right cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_MO_cgh_l	AU	float	Weighted-mean MO in tract left parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_MO_cgh_r	AU	float	Weighted-mean MO in tract right parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_MO_cst_l	AU	float	Weighted-mean MO in tract left corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_MO_cst_r	AU	float	Weighted-mean MO in tract right corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_MO_fma	AU	float	Weighted-mean MO in tract forceps major (from dMRI data)
IDP_dMRI_ProbtrackX_MO_fmi	AU	float	Weighted-mean MO in tract forceps minor (from dMRI data)
IDP_dMRI_ProbtrackX_MO_ifo_l	AU	float	Weighted-mean MO in tract left inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MO_ifo_r	AU	float	Weighted-mean MO in tract right inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MO_ilf_l	AU	float	Weighted-mean MO in tract left inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MO_ilf_r	AU	float	Weighted-mean MO in tract right inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MO_mcp	AU	float	Weighted-mean MO in tract middle cerebellar peduncle (from dMRI data)
IDP_dMRI_ProbtrackX_MO_ml_l	AU	float	Weighted-mean MO in tract left medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_MO_ml_r	AU	float	Weighted-mean MO in tract right medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_MO_ptr_l	AU	float	Weighted-mean MO in tract left posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MO_ptr_r	AU	float	Weighted-mean MO in tract right posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MO_slf_l	AU	float	Weighted-mean MO in tract left superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MO_slf_r	AU	float	Weighted-mean MO in tract rigt superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MO_str_l	AU	float	Weighted-mean MO in tract left superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MO_str_r	AU	float	Weighted-mean MO in tract right superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_MO_unc_l	AU	float	Weighted-mean MO in tract left uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_MO_unc_r	AU	float	Weighted-mean MO in tract right uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L1_ar_l	AU	float	Weighted-mean L1 in tract left acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L1_ar_r	AU	float	Weighted-mean L1 in tract right acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L1_atr_l	AU	float	Weighted-mean L1 in tract left anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L1_atr_r	AU	float	Weighted-mean L1 in tract right anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L1_cgc_l	AU	float	Weighted-mean L1 in tract left cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_L1_cgc_r	AU	float	Weighted-mean L1 in tract right cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_L1_cgh_l	AU	float	Weighted-mean L1 in tract left parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_L1_cgh_r	AU	float	Weighted-mean L1 in tract right parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_L1_cst_l	AU	float	Weighted-mean L1 in tract left corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_L1_cst_r	AU	float	Weighted-mean L1 in tract right corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_L1_fma	AU	float	Weighted-mean L1 in tract forceps major (from dMRI data)
IDP_dMRI_ProbtrackX_L1_fmi	AU	float	Weighted-mean L1 in tract forceps minor (from dMRI data)
IDP_dMRI_ProbtrackX_L1_ifo_l	AU	float	Weighted-mean L1 in tract left inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L1_ifo_r	AU	float	Weighted-mean L1 in tract right inferior fronto-occipital fasciculus (from dMRI data)

IDP_dMRI_ProbtrackX_L1_ilf_l	AU	float	Weighted-mean L1 in tract left inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L1_ilf_r	AU	float	Weighted-mean L1 in tract right inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L1_mcp	AU	float	Weighted-mean L1 in tract middle cerebellar peduncle (from dMRI data)
IDP_dMRI_ProbtrackX_L1_ml_l	AU	float	Weighted-mean L1 in tract left medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_L1_ml_r	AU	float	Weighted-mean L1 in tract right medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_L1_ptr_l	AU	float	Weighted-mean L1 in tract left posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L1_ptr_r	AU	float	Weighted-mean L1 in tract right posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L1_slf_l	AU	float	Weighted-mean L1 in tract left superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L1_slf_r	AU	float	Weighted-mean L1 in tract rigt superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L1_str_l	AU	float	Weighted-mean L1 in tract left superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L1_str_r	AU	float	Weighted-mean L1 in tract right superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L1_unc_l	AU	float	Weighted-mean L1 in tract left uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L1_unc_r	AU	float	Weighted-mean L1 in tract right uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L2_ar_l	AU	float	Weighted-mean L2 in tract left acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L2_ar_r	AU	float	Weighted-mean L2 in tract right acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L2_atr_l	AU	float	Weighted-mean L2 in tract left anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L2_atr_r	AU	float	Weighted-mean L2 in tract right anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L2_cgc_l	AU	float	Weighted-mean L2 in tract left cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_L2_cgc_r	AU	float	Weighted-mean L2 in tract right cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_L2_cgh_l	AU	float	Weighted-mean L2 in tract left parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_L2_cgh_r	AU	float	Weighted-mean L2 in tract right parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_L2_cst_l	AU	float	Weighted-mean L2 in tract left corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_L2_cst_r	AU	float	Weighted-mean L2 in tract right corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_L2_fma	AU	float	Weighted-mean L2 in tract forceps major (from dMRI data)
IDP_dMRI_ProbtrackX_L2_fmi	AU	float	Weighted-mean L2 in tract forceps minor (from dMRI data)
IDP_dMRI_ProbtrackX_L2_ifo_l	AU	float	Weighted-mean L2 in tract left inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L2_ifo_r	AU	float	Weighted-mean L2 in tract right inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L2_ilf_l	AU	float	Weighted-mean L2 in tract left inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L2_ilf_r	AU	float	Weighted-mean L2 in tract right inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L2_mcp	AU	float	Weighted-mean L2 in tract middle cerebellar peduncle (from dMRI data)
IDP_dMRI_ProbtrackX_L2_ml_l	AU	float	Weighted-mean L2 in tract left medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_L2_ml_r	AU	float	Weighted-mean L2 in tract right medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_L2_ptr_l	AU	float	Weighted-mean L2 in tract left posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L2_ptr_r	AU	float	Weighted-mean L2 in tract right posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L2_slf_l	AU	float	Weighted-mean L2 in tract left superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L2_slf_r	AU	float	Weighted-mean L2 in tract rigt superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L2_str_l	AU	float	Weighted-mean L2 in tract left superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L2_str_r	AU	float	Weighted-mean L2 in tract right superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L2_unc_l	AU	float	Weighted-mean L2 in tract left uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L2_unc_r	AU	float	Weighted-mean L2 in tract right uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L3_ar_l	AU	float	Weighted-mean L3 in tract left acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L3_ar_r	AU	float	Weighted-mean L3 in tract right acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L3_atr_l	AU	float	Weighted-mean L3 in tract left anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L3_atr_r	AU	float	Weighted-mean L3 in tract right anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L3_cgc_l	AU	float	Weighted-mean L3 in tract left cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_L3_cgc_r	AU	float	Weighted-mean L3 in tract right cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_L3_cgh_l	AU	float	Weighted-mean L3 in tract left parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_L3_cgh_r	AU	float	Weighted-mean L3 in tract right parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_L3_cst_l	AU	float	Weighted-mean L3 in tract left corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_L3_cst_r	AU	float	Weighted-mean L3 in tract right corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_L3_fma	AU	float	Weighted-mean L3 in tract forceps major (from dMRI data)
IDP_dMRI_ProbtrackX_L3_fmi	AU	float	Weighted-mean L3 in tract forceps minor (from dMRI data)
IDP_dMRI_ProbtrackX_L3_ifo_l	AU	float	Weighted-mean L3 in tract left inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L3_ifo_r	AU	float	Weighted-mean L3 in tract right inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L3_ilf_l	AU	float	Weighted-mean L3 in tract left inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L3_ilf_r	AU	float	Weighted-mean L3 in tract right inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L3_mcp	AU	float	Weighted-mean L3 in tract middle cerebellar peduncle (from dMRI data)
IDP_dMRI_ProbtrackX_L3_ml_l	AU	float	Weighted-mean L3 in tract left medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_L3_ml_r	AU	float	Weighted-mean L3 in tract right medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_L3_ptr_l	AU	float	Weighted-mean L3 in tract left posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L3_ptr_r	AU	float	Weighted-mean L3 in tract right posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L3_slf_l	AU	float	Weighted-mean L3 in tract left superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L3_slf_r	AU	float	Weighted-mean L3 in tract rigt superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L3_str_l	AU	float	Weighted-mean L3 in tract left superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L3_str_r	AU	float	Weighted-mean L3 in tract right superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_L3_unc_l	AU	float	Weighted-mean L3 in tract left uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_L3_unc_r	AU	float	Weighted-mean L3 in tract right uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_ar_l	AU	float	Weighted-mean ICVF in tract left acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_ar_r	AU	float	Weighted-mean ICVF in tract right acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_atr_l	AU	float	Weighted-mean ICVF in tract left anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_atr_r	AU	float	Weighted-mean ICVF in tract right anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_cgc_l	AU	float	Weighted-mean ICVF in tract left cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_cgc_r	AU	float	Weighted-mean ICVF in tract right cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_cgh_l	AU	float	Weighted-mean ICVF in tract left parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_cgh_r	AU	float	Weighted-mean ICVF in tract right parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_cst_l	AU	float	Weighted-mean ICVF in tract left corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_cst_r	AU	float	Weighted-mean ICVF in tract right corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_fma	AU	float	Weighted-mean ICVF in tract forceps major (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_fmi	AU	float	Weighted-mean ICVF in tract forceps minor (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_ifo_l	AU	float	Weighted-mean ICVF in tract left inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_ifo_r	AU	float	Weighted-mean ICVF in tract right inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_ilf_l	AU	float	Weighted-mean ICVF in tract left inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_ilf_r	AU	float	Weighted-mean ICVF in tract right inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_mcp	AU	float	Weighted-mean ICVF in tract middle cerebellar peduncle (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_ml_l	AU	float	Weighted-mean ICVF in tract left medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_ml_r	AU	float	Weighted-mean ICVF in tract right medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_ptr_l	AU	float	Weighted-mean ICVF in tract left posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_ptr_r	AU	float	Weighted-mean ICVF in tract right posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_slf_l	AU	float	Weighted-mean ICVF in tract left superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_slf_r	AU	float	Weighted-mean ICVF in tract rigt superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_str_l	AU	float	Weighted-mean ICVF in tract left superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_str_r	AU	float	Weighted-mean ICVF in tract right superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_unc_l	AU	float	Weighted-mean ICVF in tract left uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ICVF_unc_r	AU	float	Weighted-mean ICVF in tract right uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_OD_ar_l	AU	float	Weighted-mean OD in tract left acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_OD_ar_r	AU	float	Weighted-mean OD in tract right acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_OD_atr_l	AU	float	Weighted-mean OD in tract left anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_OD_atr_r	AU	float	Weighted-mean OD in tract right anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_OD_cgc_l	AU	float	Weighted-mean OD in tract left cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_OD_cgc_r	AU	float	Weighted-mean OD in tract right cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_OD_cgh_l	AU	float	Weighted-mean OD in tract left parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_OD_cgh_r	AU	float	Weighted-mean OD in tract right parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_OD_cst_l	AU	float	Weighted-mean OD in tract left corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_OD_cst_r	AU	float	Weighted-mean OD in tract right corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_OD_fma	AU	float	Weighted-mean OD in tract forceps major (from dMRI data)
IDP_dMRI_ProbtrackX_OD_fmi	AU	float	Weighted-mean OD in tract forceps minor (from dMRI data)
IDP_dMRI_ProbtrackX_OD_ifo_l	AU	float	Weighted-mean OD in tract left inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_OD_ifo_r	AU	float	Weighted-mean OD in tract right inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_OD_ilf_l	AU	float	Weighted-mean OD in tract left inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_OD_ilf_r	AU	float	Weighted-mean OD in tract right inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_OD_mcp	AU	float	Weighted-mean OD in tract middle cerebellar peduncle (from dMRI data)
IDP_dMRI_ProbtrackX_OD_ml_l	AU	float	Weighted-mean OD in tract left medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_OD_ml_r	AU	float	Weighted-mean OD in tract right medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_OD_ptr_l	AU	float	Weighted-mean OD in tract left posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_OD_ptr_r	AU	float	Weighted-mean OD in tract right posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_OD_slf_l	AU	float	Weighted-mean OD in tract left superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_OD_slf_r	AU	float	Weighted-mean OD in tract rigt superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_OD_str_l	AU	float	Weighted-mean OD in tract left superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_OD_str_r	AU	float	Weighted-mean OD in tract right superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_OD_unc_l	AU	float	Weighted-mean OD in tract left uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_OD_unc_r	AU	float	Weighted-mean OD in tract right uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_ar_l	AU	float	Weighted-mean ISOVF in tract left acoustic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_ar_r	AU	float	Weighted-mean ISOVF in tract right acoustic radiation (from dMRI data)

IDP_dMRI_ProbtrackX_ISOVF_atr_l	AU	float	Weighted-mean ISOVF in tract left anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_atr_r	AU	float	Weighted-mean ISOVF in tract right anterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_cgc_l	AU	float	Weighted-mean ISOVF in tract left cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_cgc_r	AU	float	Weighted-mean ISOVF in tract right cingulate gyrus part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_cgh_l	AU	float	Weighted-mean ISOVF in tract left parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_cgh_r	AU	float	Weighted-mean ISOVF in tract right parahippocampal part of cingulum (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_cst_l	AU	float	Weighted-mean ISOVF in tract left corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_cst_r	AU	float	Weighted-mean ISOVF in tract right corticospinal tract (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_fma	AU	float	Weighted-mean ISOVF in tract forceps major (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_fmi	AU	float	Weighted-mean ISOVF in tract forceps minor (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_ifo_l	AU	float	Weighted-mean ISOVF in tract left inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_ifo_r	AU	float	Weighted-mean ISOVF in tract right inferior fronto-occipital fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_ilf_l	AU	float	Weighted-mean ISOVF in tract left inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_ilf_r	AU	float	Weighted-mean ISOVF in tract right inferior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_mcp	AU	float	Weighted-mean ISOVF in tract middle cerebellar peduncle (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_ml_l	AU	float	Weighted-mean ISOVF in tract left medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_ml_r	AU	float	Weighted-mean ISOVF in tract right medial lemniscus (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_ptr_l	AU	float	Weighted-mean ISOVF in tract left posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_ptr_r	AU	float	Weighted-mean ISOVF in tract right posterior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_slf_l	AU	float	Weighted-mean ISOVF in tract left superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_slf_r	AU	float	Weighted-mean ISOVF in tract rigt superior longitudinal fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_str_l	AU	float	Weighted-mean ISOVF in tract left superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_str_r	AU	float	Weighted-mean ISOVF in tract right superior thalamic radiation (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_unc_l	AU	float	Weighted-mean ISOVF in tract left uncinate fasciculus (from dMRI data)
IDP_dMRI_ProbtrackX_ISOVF_unc_r	AU	float	Weighted-mean ISOVF in tract right uncinate fasciculus (from dMRI data)

Additional IDPs:
Low-dimensional rfMRI network matrices: 210 functional edge strengths
High-dimensional rfMRI network matrices: 1485 functional edge strengths
Low-dimensional rfMRI component (node) amplitudes: 21 amplitudes
High-dimensional rfMRI component (node) amplitudes: 55 amplitudes

Total: 2501 IDPs