White matter hyperintensities classified according to intensity and spatial location reveal specific associations with cognitive performance

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A B S T R A C T
White matter hyperintensities (WMHs) on T2-weighted images are radiological signs of cerebral small vessel disease. As their total volume is variably associated with cognition, a new approach that integrates multiple radiological criteria is warranted. Location may matter, as periventricular WMHs have been shown to be associated with cognitive impairments. WMHs that appear as hypointense in T1-weighted images (T1w) may also indicate the most severe component of WMHs. We developed an automatic method that sub-classifies WMHs into four categories (periventricular/deep and T1w-hypointense/nonT1w-hypointense) using MRI data from 684 community-dwelling older adults from the Whitehall II study. To test if location and intensity information can impact cognition, we derived two general linear models using either overall or subdivided volumes. Results showed that periventricular T1w-hypointense WMHs were significantly associated with poorer performance in the trail making A (p = 0.011), digit symbol (p = 0.028) and digit coding (p = 0.009) tests. We found no association between total WMH volume and cognition. These findings suggest that sub-classifying WMHs according to both location and intensity in T1w reveals specific associations with cognitive performance.

1. Introduction

White matter hyperintensities (WMHs) on T2-weighted magnetic resonance images (MRI) are radiological signs of cerebral small vessel disease (SVD) (Wardlaw et al., 2013). They are associated with a higher incidence of stroke and dementia (Debette and Markus, 2010), mood disorders, motor impairments and urinary incontinence (Poggesi et al., 2011). Moreover, WMHs are related to cognitive impairments, particularly executive dysfunctions and poorer psychomotor speed (Bolandzadeh et al., 2012). Whilst WMHs have acquired considerable interest in the field of translational and clinical research, the assessment and the reporting of WMH volume are often inconsistent in research studies and medical practice (Frey et al., 2019).

The optimal MRI sequence to assess WMHs is fluid-attenuated inversion recovery (FLAIR). This sequence generates T2-weighted images where the signal from the cerebrospinal fluid is suppressed and hyperintense regions stand out on a low intensity homogeneous background (Wardlaw et al., 2013). In research, quantification of WMHs is...
preferred to qualitative assessment due to higher reliability, sensitivity and objectivity of the former (De Guio et al., 2016; Van den Heuvel et al., 2006) and the widespread availability of segmentation software. However, the interpretation of quantitative results and comparison between studies remain difficult due to acquisition-related differences (scanner, protocol), discrepancies between processing methods (pre-processing pipelines, method/tool used to extract WMH measurements) and variations in the definition of what should be considered a WMH (De Guio et al., 2016). Harmonisation methods that reduce or compensate for the variability due to acquisition differences and/or processing discrepancies are being developed to enable comparisons between or pooling of MRI-derived measures from different datasets (Bordin et al., 2020). Notwithstanding, the lack of a clear definition on what should be segmented as a WMH and whether some WMH sub-classes are more clinically relevant than others warrants further investigation (Alber et al., 2019; Frey et al., 2019; Murray et al., 2010; Smith et al., 2019; Tate et al., 2008; Wardlaw et al., 2013).

Periventricular WMHs are more strongly associated with concurrent cognitive deficits than deep ones (Bolandzadeh et al., 2012). This is in line with longitudinal studies on regional baseline WMH volumes and their association with the risk of transition from intact cognition to mild cognitive impairment and dementia (De Groot et al., 2002; Kim et al., 2015; van Straaten et al., 2008). To explain this finding, the hypothesis of reduced brain reserve in periventricular regions has been put forward (De Groot et al., 2002). Despite this evidence, it is still unclear whether periventricular and deep WMHs would constitute a continuous entity or should be considered and reported separately (DeCarli et al., 2005). If line with longitudinal studies on regional baseline WMH volumes and current cognitive function were assessed at the time of the MRI. MRI data were acquired at the Oxford Centre for Functional MRI of the Brain (FMRIB), Wellcome Centre for Integrative Neuroimaging (University of Oxford), using a 3-T Siemens Magneton Verio (Erlangen, Germany) scanner with a 32-channel receive head coil from April 2012 to December 2014 (N = 550 participants) and a 3-T Siemens Prisma (Erlangen, Germany) with a 64-channel receive head-neck coil from July 2015 to December 2016 (N = 250 participants) due to a scanner upgrade. Details of acquisition protocols are shown in (Filippini et al., 2014) and (Zoldos et al., 2020) and are reported in Supplementary Table S1. For the purpose of this study we used high-resolution T1-weighted images, FLAIR images and diffusion weighted images (DWI).

All images were processed and analysed using FMRIB Software Library (FSL) v6.0 tools (Jenkinson et al., 2012). Participants’ T1-weighted and FLAIR images were skull-stripped with FSL-BET (Smith, 2002) and bias field corrected with FSL-FAST (Zhang et al., 2001). DWI scans were pre-processed as described in (Filippini et al., 2014) and a diffusion tensor model was fit at each voxel to obtain maps of fractional anisotropy (FA), mean diffusivity (MD), axial diffusivity (AD) and radial diffusivity (RD). T1-weighted and FA images were then linearly registered to the corresponding FLAIR with FSL-FLIRT (Jenkinson and Smith, 2001). WMHs segmentation was performed with FSL-BIANCA (Griffanti et al., 2016), using intensity features (T1-weighted and FLAIR), local average intensities (3 voxels kernel), and spatial features (MNI coordinates obtained from the transformation between FLAIR and MNI for each subject, weighting factor of 2). To avoid scanner-specific biases in the estimates, BIANCA was trained with WMH masks manually delineated in a sub-sample of individuals scanned on the Prisma (n = 24) and Verio (n = 24) scanners and an independent sample from the UK Biobank study (n = 12). The processing steps and the training settings have been previously optimised (Bordin et al., 2020) to offer the best balance between segmentation performance and removal of scanner-specific biases in the WMH estimates. The total WMH mask included voxels exceeding a probability of 0.9 of being a WMH and located within a white matter mask as described in (Griffanti et al., 2016). Finally, WMH masks were visually checked by an experienced observer to exclude images where small segmentation errors could hinder subsequent WMH sub-classification. The total WMH mask included voxels exceeding a probability of 0.9 of being a WMH and located within a white matter mask as described in (Griffanti et al., 2016). The total WMH volume was adjusted for the total brain volume and log transformed for statistical analysis.

We separated WMHs voxels into T1-hypointense and non T1-hypointense. To achieve this, we used FSL-FAST (Zhang et al., 2001) on T1-weighted images to perform tissue type segmentation and calculate maps of partial volume estimates (PVE) for the three classes (grey intensity in T2-weighted images that was automatic and objective and used multiple linear regression analysis to see if these WMH sub-classes show specific associations with validated scores of cognitive functions. Given the current limitations and discrepancies in WMHs definition, our ultimate goal was to identify which sub-class(es) are specifically linked to cognitive function. This would inform future guidelines to focus the assessment on clinically-relevant radiological criteria of WMHs beyond their total extent, with a clear and objective definition of WMHs radiological appearance and location.
matter, white matter and cerebrospinal fluid). Due to their low-intensity values, T₁-hypointense WMHs are classified by FAST as either grey matter or cerebrospinal fluid. We therefore classified voxels as non T₁-hypointense WMHs the voxels within the total WMH mask where the corresponding white matter PVE was greater than 0.5. We then obtained T₁-hypointense WMHs by subtraction.

We used a cluster-based approach to separate between periventricular and deep WMHs, similar to the “continuity to ventricle” criterion described by (Griffanti et al., 2018). To do so, we created an extended ventricle mask (i.e. a ventricle mask that extended beyond the ventricular boundaries) in the Montreal Neurological Institute (MINI) space. The extended ventricle mask consisted of the probability maps -set with a very low threshold- of the lateral ventricles, thalami and fornix bilaterally. We transformed the mask to the single-subject FLAIR space via the corresponding T₁-weighted intensity-based classification of WMHs by non-linear registration (Andersson et al., 2007), and classified as periventricular WMHs the clusters that overlapped with any part of the mask. Deep WMHs were then defined by subtraction.

We finally combined the two criteria and obtained four WMH masks for the following sub-classes for each participant: periventricular T₁-hypointense WMHs; periventricular non T₁-hypointense WMHs; deep T₁-hypointense WMHs; deep non T₁-hypointense WMHs. Then, each mask was used to derive the corresponding WMH volume, which was adjusted for the total brain volume and log transformed for statistical analysis.

We performed univariate multiple linear regression using the univariate general linear model function type III sum of squares on SPSS version 25.0 (IBM Corp. Armonk, NY). The following measures of participants’ cognition were selected as indices of global functioning, executive function, processing speed, working memory and word retrieval, in line with (Bolandzadeh et al., 2012): Montreal cognitive assessment (MoCA), trail-making test (TMT, A and B), digit span forward, backwards and sequence, digit symbol, digit coding, Boston naming-60 test (BNT), phonemic (letter) fluency (FLU-L) and semantic (category) fluency (FLU-C) tests. For details on the cognitive tests please refer to (Filippini et al., 2014). Demographic variables (age at the examination, sex, total years of education, systolic blood pressure, diastolic blood pressure) were used as covariates of no interest. For each cognitive test (dependent variable in the univariate multiple linear regression), two models were investigated, in which participants’ demographic variables were kept unchanged while WMHs were included as either WMHs total volume (corresponding to the BIANCA output) or subdivided WMH volumes (corresponding to the four sub-classes reported above).

To better investigate the meaning of T₁-hypointensity in our sample, we performed two post-hoc analyses. First, we studied WMH microstructure using DTI-derived metrics, given the lack of histopathological data for this dataset. Accordingly, we compared T₁-hypointense and non T₁-hypointense WMHs in terms of average fractional anisotropy (FA), mean diffusivity (MD), axial diffusivity (AD) and radial diffusivity (RD) using paired t-tests to evaluate potential differences in the underlying microstructure. Second, since we noticed that a WMH often includes both T₁-hypointense and non T₁-hypointense voxels, we adopted an alternative T₁-weighted intensity-based classification of WMHs by dividing the total WMH map into WMH clusters with and without T₁-hypointense voxels. This sub-classification was then used to look at the prevalence of WMH clusters with a T₁-hypointense component and to better interpret the results of the main analysis.

We also used Pearson correlations to further investigate the associations between WMH sub-classes, total WMH volume and age.

Statistical significance was set at α = 0.05. Further correction for multiple hypotheses testing was performed using Bonferroni correction (Di Leo and Sardanelli, 2020).

3. Results

Participants characteristics (demographics, cognitive scores and MRI measures) are reported in Table 1. One hundred and sixteen participants were excluded from our analysis due to incomplete or poor-quality images (N = 44), neurological disorders (N = 30) and inaccurate WMH segmentation masks (N = 42) to leave a total of 684 community-dwelling older adults. Participants’ age ranged from 60 to 83 years. Most of participants were male (551/684, 81%) and had a MoCA score greater than or equal to 26 (551/684, 81%).

An example of the WMH segmentation output resulting from the method we developed is provided in Fig. 1.

White matter hyperintensities expressed as total volume were not significantly associated with any of the cognitive tests. However, when the four sub-classes of WMHs were instead used in the model, we found statistically significant associations between periventricular T₁-hypointense WMHs and poorer performance on the TMT-A (p = 0.011), digit symbol (p = 0.028) and digit coding (p = 0.009) tests. Conversely, non T₁-hypointense periventricular WMHs were associated with higher scores on the digit backwards test (p = 0.023). Also, deep non T₁-hypointense WMHs were found to be positively associated with the

| Table 1 | Sample characteristics. |
|---------|-------------------------|
| **Descriptive statistics** | N | Minimum | Maximum | Mean | Standard deviation |
| Demographics | | | | | |
| Age (years) | 684 | 60.34 | 83.03 | 69.65 | 5.06 |
| Sex (M:F) | 551:133 | | | | |
| Total education (years) | 684 | 13 | 28 | 19.10 | 2.85 |
| Systolic blood pressure (mmHg) | 681 | 93 | 226 | 141.09 | 17.54 |
| Diastolic blood pressure (mmHg) | 680 | 47 | 114 | 77.21 | 10.77 |
| Cognitive scores | | | | | |
| MoCA | 684 | 17 | 30 | 27.25 | 2.25 |
| Trail making A | 682 | 13 | 125 | 30.98 | 11.73 |
| Trail making B | 680 | 24 | 321 | 67.08 | 33.84 |
| Trail making B-A | 680 | 8 | 253 | 36.25 | 28.73 |
| Digit span forward | 683 | 5 | 16 | 11.08 | 2.28 |
| Digit span backwards | 683 | 4 | 16 | 9.65 | 2.45 |
| Digit span sequence | 683 | 0 | 16 | 10.05 | 2.48 |
| Digit symbol | 683 | 13 | 46 | 30.78 | 5.75 |
| Digit coding | 683 | 13 | 114 | 63.02 | 13.22 |
| Boston naming test-60 | 684 | 15 | 60 | 57.38 | 4.66 |
| Letter fluency | 684 | 3 | 31 | 15.78 | 4.64 |
| Category fluency | 684 | 3 | 40 | 22.36 | 5.34 |

| MRI measures | | | | | |
| Total brain volume (dm³) | 684 | 1.023 | 1.928 | 1.456 | 0.133 |
| Total WMH volume (cm³) | 684 | 0.339 | 35.627 | 5.855 | 3.715 |
| Periventricular T₁-hypointense WMHs (cm³) | 684 | 0.240 | 31.448 | 2.679 | 3.025 |
| Periventricular non T₁-hypointense WMHs (cm³) | 684 | 0.050 | 6.379 | 2.138 | 0.831 |
| Deep T₁-hypointense WMHs (cm³) | 684 | 0.001 | 5.274 | 0.434 | 0.577 |
| Deep non T₁-hypointense WMHs (cm³) | 684 | 0.003 | 3.976 | 0.604 | 0.565 |

Legend: MoCA, Montreal cognitive assessment; WMHs, white matter hyperintensities.
letter \((p = 0.004)\) and category \((p = 0.036)\) fluency tests. Regression analysis results for the models where WMHs sub-classes were significantly associated with cognitive performances are shown in Table 2. Comprehensive results for all the models, including all covariates, are showed in Supplementary Table S2.

When looking at microstructural differences in WMHs classified according to the intensity in T\(_1\)-weighted images criterion, T\(_1\)-hypointense WMHs showed significantly lower FA, and higher MD, AD and RD than non T\(_1\)-hypointense WMHs \((p < 0.001\) for all measures). Results of the within-subject paired \(t\)-tests for the averages of DTI-derived metrics between T\(_1\)- and non T\(_1\)-hypointense WMHs are reported in Table 3.

Results for the separation of the total WMH volume into WMH clusters with and without corresponding T\(_1\)-hypointense voxels are reported in Table 4.

We found that 50% of the WMH clusters had T\(_1\)-hypointense voxels. However, despite constituting half of all clusters, these WMH clusters with at least one T\(_1\)-hypointense voxel composed 94% of the whole WMH volume. The remaining 6% of the WMH volume consisted of small non T\(_1\)-hypointense WMH clusters, i.e. WMH clusters without co-located

![Fig. 1. The left panel shows the native images (FLAIR and T\(_1\)-weighted) and image processing outputs (WMH total and WMH sub-classes) for a subject drawn from the study sample. The right panel shows a colour-coded detailed view of the four sub-classes of WMHs.](image)

### Table 2

Multiple linear regression analysis results. Model results and significant WMH predictors of cognitive scores adjusted for age at the examination, sex, total years of education, systolic blood pressure and diastolic blood pressure.

| Cognitive test          | Model | Parameter estimates          |
|-------------------------|-------|-----------------------------|
|                         | F     | \(p\)-value | Adjusted \(R^2\) | Significant WMH covariate | \(\beta\) (SE) | \(p\)-value \(^a\) |
| Trail making A          | 10.08 | \(<0.001\) | 0.11 | T\(_1\)-hypointense periventricular WMHs | 4.79 (1.87) | 0.011 |
| Digit span backwards    | 5.92  | \(<0.001\) | 0.06 | Non T\(_1\)-hypointense periventricular WMHs | 1.30 (0.57) | 0.023 |
| Digit span sequence     | 4.99  | \(<0.001\) | 0.05 | T\(_1\)-hypointense periventricular WMHs | \(-0.79 (0.41)\) | 0.054 |
| Digit symbol            | 8.25  | \(<0.001\) | 0.09 | T\(_1\)-hypointense periventricular WMHs | \(-2.05 (0.93)\) | 0.028 |
| Digit coding            | 11.06 | \(<0.001\) | 0.12 | T\(_1\)-hypointense periventricular WMHs | \(-5.52 (2.09)\) | 0.009 |
| Letter fluency          | 3.74  | \(<0.001\) | 0.04 | Non T\(_1\)-hypointense deep WMHs | 2.10 (0.72) | 0.004 |
| Category fluency        | 8.07  | \(<0.001\) | 0.09 | Non T\(_1\)-hypointense deep WMHs | 1.83 (0.87) | 0.036 |

Legend: SE, standard error; WMHs, white matter hyperintensities.

\(^a\): \(P\)-values did not remain significant after adjustment for multiple comparisons across cognitive tests.

\(^*\): Predictor that shows a trend for significance \((0.05 < p < 0.06)\).
predictors for the participants linear regression models using the volumes of WMH sub-classes as in the Alzheimer Disease Neuroimaging Initiative dataset was also WMHs were found to be more strongly associated with participants ( De Groot et al., 2002; Griffanti et al., 2018 ), where periventricular processing speed. The method could predominantly prove useful in healthy elderly. Subjects global functioning scores within normal limits, our sub-classification performance on multiple cognitive tests, including the trail making A, and higher scores at the fluency tests. Since the volume of non T1-hypointense voxels ( T1-hypointense clusters) from those that did not (non T1-hypointense clusters) ( Table 4 ). Since most of the WMH volume comprised (relatively big) clusters with a T1-hypointense component, our results suggest that the evolution of a WMH may be a cascade of events starting from small punctate lesions leading to bigger lesions with a T1-hypointense core and surrounding non T1-hypointense rim (Fig. 2). This mechanism could explain the significant association we observed between higher volume of deep non T1-hypointense WMHs and higher scores at the fluency tests. Since the volume of non T1-hypointense WMHs includes both the volume of non T1-hypointense clusters and the outer rim of the clusters with a T1-hypointense core, we hypothesized that the positive association of deep non T1-hypointense WMHs with higher cognitive scores at the fluency tests could be driven by non-T1 hypointense clusters (i.e. smaller, less severe WMHs, that have not yet progressed into a WMH with a T1-hypointense component). We tested this hypothesis by fitting multiple linear regression models with either of these two components as the only WMH predictor for the fluency tests ( Supplementary Table S3 ). Notably, non T1-hypointense clusters were more strongly associated with fluency scores than deep non T1-hypointense WMHs. Thus, it is likely that the volume of clusters of non T1-hypointense WMHs drove the observed significance of deep non T1-hypointense WMHs as predictors of better cognitive scores at the fluency tests.

The positive associations of non T1-hypointense clusters with fluency scores could be due to the fact that these small lesions are more frequent in younger individuals with a low WMH volume. The hypothesized evolution into T1-hypointense clusters would then explain the apparent decrease of this type of lesions in individuals with lower fluency scores. Since non T1-hypointense clusters are small, we cannot exclude the possibility that some of these are false positives from BIANCA segmentation. However, WMH masks have been visually checked so that it is

**Table 4**

| Number and size of WMH clusters with and without T1-hypointense voxels. |
|-------------------------------|------------------|------------------|
| WMH clusters                  | Average volume   | Average volume   |
|                               | per subject (cm³) | per cluster (mm³) |
| Clusters without T1-hypointense voxels | 223.91 ± 103.77 | 5.86 ± 3.72 | 36 ± 42 |
| Clusters with T1-hypointense voxels | 112.43 ± 59.43 | 0.30 ± 0.19 | 3 ± 1 |
| Rims                          | 111.48 ± 57.55  | 5.56 ± 3.75 | 66 ± 63 |
| Cores                         | 2.45 ± 1.02     | 28 ± 19       | 3.11 ± 3.23 | 38 ± 50 |

Legend: WMHs, white matter hyperintensities.

hypointensity in T1-weighted images.

The volume of non T1-hypointense WMHs is the sum of non T1-hypointense clusters and the hyperintense rims of T1-hypointense clusters (a schematic representation is depicted in Fig. 2).

Given the unexpected significant positive associations of non T1-hypointense WMHs with the digit span backwards, letter and category fluency, we investigated which of these two components (either non T1-hypointense clusters or rims of T1-hypointense clusters) drove the observed associations. When fitting multiple linear regression models with either of these two components as the only WMH predictor for the fluency and digit span backwards scores, we found that non T1-hypointense clusters were significantly associated with the fluency performances (FLU-L: $\beta = 1.98$, p = 0.001; FLU-C: $\beta = 2.02$, p = 0.004). Conversely, rims were significant predictors of the digit span backwards scores ($\beta = 0.92$, p = 0.035).

Additional multiple regression models and Pearson correlations among WMH sub-classes, total WMH volume and age supporting these findings are reported in Supplementary Tables S3 and S4.

**4. Discussion**

In this study we sought to provide a clinically-oriented insight into WMHs by developing an automated method for classifying WMHs according to spatial location (periventricular versus deep WMHs) and lesion intensity in the corresponding T1-weighted image (T1-hypointense versus non T1-hypointense WMHs). We fitted univariate multiple linear regression models using the volumes of WMH sub-classes as predictors for the participants’ performance in several cognitive tests and then further explored the microstructural properties of T1-hypointense WMHs to understand the meaning of this radiological appearance. Our classification proved to be clinically meaningful, as periventricular T1-hypointense WMHs were found to be linked to poorer performance on multiple cognitive tests, including thetrail making A, digit symbol and digit coding tests. Since most of participants showed global functioning scores within normal limits, our sub-classification method could predominantly prove useful in healthy elderly. Subjects without overt cognitive decline or dementia would also benefit more from prompt preventive and therapeutic interventions. Overall, our results suggest that sub-classifying WMHs according to intensity and spatial location may turn out to be useful for investigating cognitive performance in the ageing population. Notably, periventricular T1-hypointense WMHs would represent a promising WMH biomarker for investigating cognitive domains related to executive function and processing speed.

Our finding of periventricular WMHs being associated with poorer executive function and psychomotor speed scores is in line with previous large longitudinal population-based studies on non-demented elderly ( De Groot et al., 2002; Griffanti et al., 2018 ), where periventricular WMHs were found to be more strongly associated with participants’ cognition than deep WMHs. Increased volume of periventricular WMHs in the Alzheimer Disease Neuroimaging Initiative dataset was also associated with evidence of beta-amyloid deposition in the brain ( Marnane et al., 2016 ), suggesting a synergistic damage driven by concurrent SVD and Alzheimer’s pathology in these areas. Periventricular regions are also characterised by high density of long associating fibres which link the cortex to the deep grey matter and other distant brain territories ( Filley, 1998 ). For this reason, they are potentially susceptible to pathologies that damage cortical arteries and eventually provoke distal hypoperfusion ( Moody et al., 1990 ). Disrupted cholinergic activity is related to periventricular (and not deep) WMHs and may be involved in the physio-pathological pathway that underpins the observed cognitive scores ( Bohnen et al., 2009 ). Moreover, high periventricular WMHs were found to be associated with frontal cortical thinning, where both imaging findings were independently linked to executive dysfunctions ( Seo et al., 2012 ). Altogether, these findings endorse our results of periventricular WMHs being more strongly associated with domain-specific poorer cognitive performance than deep WMHs.

Although the location criterion is well established, less is known about the meaning of T1-intensity in WMHs. This aspect has been well-investigated in demyelinating disease where hypointense lesions in T1-weighted images are more likely to represent low axonal density and irreversible tissue damage ( Bitsch et al., 2001; Van Walderveen et al., 1998 ). Our DTI analysis showed decreased FA and increased MD, AD and RD in T1-hypointense WMHs. Not surprisingly, these findings mirror similar microstructural results found in multiple sclerosis ( Vavasour et al., 2019 ) and suggest more severe damage to the white matter in T1-hypointense areas than their T1-isointense counterpart. T1-hypointense and non T1-hypointense WMHs may represent two distinct entities with different meanings. Alternatively, WMHs could start as small punctate FLAIR hyperintensities and later develop a T1-hypointense “core”. Despite the lack of longitudinal data in our cohort, we attempted to investigate further the meaning of the intensity in T1-weighted images and the theoretical evolution of WMHs and their intensity in T1-weighted images from a cross-sectional basis. Within the total WMH mask, we separated WMH clusters that contained some T1-hypointense voxels ( T1-hypointense clusters) from those that did not (non T1-hypointense clusters) ( Table 4 ). Since most of the WMH volume comprised (relatively big) clusters with a T1-hypointense component, our results suggest that the evolution of a WMH may be a cascade of events starting from small punctate lesions leading to bigger lesions with a T1-hypointense core and surrounding non T1-hypointense rim (Fig. 2).
unlikely that the results could be driven by errors in WMHs segmentation.

Our finding of higher non T₁-hypointense periventricular WMHs linked to higher scores at the digit span backwards test could instead be explained by the other component of non T₁-hypointense WMHs, the non T₁-hypointense voxels belonging to T₁-hypointense clusters (i.e. the hypointense “rims”). In fact, when fitting the multiple linear regression model with the volumes of rims of all T₁-hypointense clusters as the only imaging predictor, we found a positive association with the digit span backwards that was very similar to the one given by non T₁-hypointense periventricular WMHs alone (Supplementary Table S3). Although rim and core belong to the same physical entity (i.e. the WMH cluster) they are likely to have opposite meanings. On the one hand, T₁-hypointense WMH voxels predict bad cognitive scores, as seen for the Trail Making Test A, digit symbol and digit coding tests. On the other hand, in spite of the positive association between rims and cores in terms of overall volume, the former are predictors of higher cognitive scores from the digit span backwards test. Thus, within the context of our hypothesized evolution of WMHs, rims would represent those WMH areas belonging to T₁-hypointense clusters that have not turned T₁-hypointense yet and theoretically “withstand” further tissue damage. When this occurs, the number of non T₁-hypointense voxels would decrease because they become T₁-hypointense. This would in turn explain the positive relationship with cognition observed in our results. Further investigation would be necessary to explore the potential cascade of events leading to change in T₁ intensity in a longitudinal setting, since the hypothesis of rims as WMHs associated with healthy cognitive aging is very speculative.

Our study has some limitations in terms of the data and the methodology. The Whitehall II imaging sub-study dataset shows a narrow age range (60–84 years) and a strong gender imbalance, skewed towards men, since it reflects the demographic of British civil servants at the time of recruitment in the main study. Moreover, our finding that higher periventricular WMHs are linked to poorer cognitive scores is based on the definition of periventricular WMHs as the WMHs that are contiguous with the margins of each lateral ventricle. Despite previous comparisons of different ways to define periventricular WMHs on this population giving comparable results across criteria (Griffanti et al., 2018), we cannot exclude that other sub-classification criteria may yield different results. Future work is therefore needed to test the generalisability of our findings. Furthermore, our approach for the sub-classification of WMHs relies on automated segmentation of WMHs with BIANCA, tissue type segmentation with FAST, and registration of images with different spatial resolutions. As already mentioned, we cannot exclude inaccuracies in the WMH masks, despite visual inspection of the results. We used FAST segmentation as a proxy for defining T₁-hypointensity, therefore inaccuracies in the segmentation would translate to inaccuracies in the sub-classification. Moreover, we performed linear and non-linear registrations between images with different resolutions (FLAIR, T₁ and MNI space) and the interpolation process could have slightly affected the segmented volumes.

Finally, our hypothesis on the evolution of WMHs should be interpreted cautiously and prompt further longitudinal studies. For example, it would be very valuable to follow up participants and study how WMH sub-classes evolve over time to validate the proposed theory. Another interesting future development would be looking at how the different WMH sub-classes are related to incidence of diseases, such as stroke and dementia, using risk models in well-balanced longitudinal datasets. If results are confirmed, our classification system could ultimately be translated into the clinic.

Despite these limitations, this study presents some novel theoretical and methodological insights that can contribute to better understanding of the role of WMHs in cognitive aging. The methods developed herein can be easily adopted in other research settings. The extended ventricle mask and the scripts created for images post-processing are publicly available¹. These scripts can also be equally applied to any manually- or automatically-derived WMH masks, other than those from BIANCA, to obtain the four WMH sub-classes presented in this study.

4.1. Conclusion

We showed that information from spatial location and intensity in T₁-weighted images provide potentially clinically useful insights into the meaning of WMHs with regards to participants’ cognitive function. Notably, the combination of these two criteria revealed an association with cognitive scores related to executive function, processing speed, working memory and language, that the WMH total volume alone could not provide.

CRediT authorship contribution statement

Luca Melazzini: Conceptualization, Formal analysis, Investigation, Data curation, Methodology, Software, Visualization, Writing - original draft. Clare E. Mackay: Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Visualization, Writing - review & editing. Valentina Bordin: Investigation, Methodology, Software, Writing - review & editing. Sana Suri: Investigation, Writing - review & editing. Eniko Zsoldos: Data curation, Project administration, Writing - review & editing. Abda Mahmoud: Data curation, Project administration, Writing - review & editing. Vaanathi Sundaresan: Methodology, Software, Writing - review & editing. Marina Codari: Supervision, Writing - review & editing. Eugene Duff: Investigation, Methodology,

¹ Git repository: https://git.fmrib.ox.ac.uk/ludovica/wmh-sub-classes
Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.nicl.2021.102616.
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