Brain Structure and Function (2019) 224:337–350
https://doi.org/10.1007/s00429-018-1770-6

ORIGINAL ARTICLE

Relating individual differences in white matter pathways to children's arithmetic fluency: a spherical deconvolution study

Brecht Polspoel[1] · Maaike Vandermosten[2] · Bert De Smedt[1]

Received: 8 June 2018 / Accepted: 2 October 2018 / Published online: 13 October 2018

Abstract

Connectivity between brain regions is integral to efficient complex cognitive processing, making the study of white matter pathways in clarifying the neural mechanisms of individual differences in arithmetic abilities critical. This white matter connectivity underlying arithmetic has only been investigated through classic diffusion tensor imaging, which, due to methodological limitations, might lead to an oversimplification of the underlying anatomy. More complex non-tensor models, such as spherical deconvolution, however, allow a much more fine-grained delineation of the underlying brain anatomy. Against this background, the current study is the first to use spherical deconvolution to investigate white matter tracts and their relation to individual differences in arithmetic fluency in typically developing children. Participants were 48 typically developing 9–10-year-olds, who were all in grade 4, and who underwent structural diffusion-weighted magnetic resonance imaging scanning. Theoretically relevant white matter tracts were manually delineated with a region of interest approach, after which the hindrance modulated orientational anisotropy (HMOA) index, which provides information on the structural integrity of the tract at hand, was derived for each tract. These HMOA indices were correlated with measures of arithmetic fluency, using frequentist and Bayesian approaches. Our results point towards an association between the HMOA of the right inferior longitudinal fasciculus and individual differences in arithmetic fluency. This might reflect the efficiency with which children process Arabic numerals. Other previously found associations between white matter and individual differences in arithmetic fluency were not observed.

Keywords Arithmetic · Children · Diffusion tensor imaging · Spherical deconvolution · Inferior longitudinal fasciculus

Introduction

Many studies have investigated the neural basis of arithmetic. Accumulating evidence in adults points towards a fronto-parietal network, including superior and inferior parietal lobes, inferior frontal gyri and the insular cortex, as being consistently activated during arithmetic (for a review, see Arsalidou and Taylor 2011; Menon 2015). In children, this arithmetic network involves a large set of bilateral areas, including frontal (both ventro- and dorsolateral prefrontal cortex), parietal (intraparietal sulcus, angular gyrus, and supramarginal gyrus), occipito-temporal and medial temporal (including the hippocampus) areas (Peters and De Smedt 2018, for a review; Arsalidou et al. 2018, for a meta-analysis). Furthermore, arithmetic development is characterized by a decreasing engagement of the prefrontal cortex and by an increasing engagement and functional specialization of the inferior and posterior parietal cortex (Kucian et al. 2008; Rivera et al. 2005). This shift has been interpreted as

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s00429-018-1770-6) contains supplementary material, which is available to authorized users.

✉ Brecht Polspoel
brecht.polspoel@kuleuven.be

Maaike Vandermosten
maaike.vandermosten@kuleuven.be

Bert De Smedt
bert.desmedt@kuleuven.be

1 Parenting and Special Education Research Unit, KU Leuven, Leopold Vanderkelenstraat 32, box 3765, 3000 Leuven, Belgium

2 Experimental ORL, Department of Neurosciences, KU Leuven, box 721, Herestraat 49, 3000 Leuven, Belgium

reflecting a change in strategy use, from demanding procedural manipulations to fast automated processing; a hypothesis that has recently been confirmed on the neural level (Polspoel et al. 2017). Finally, within arithmetic, large individual differences exist on a behavioral level, which have also been established on the neural level, in both adults (Grabner et al. 2007) and children (De Smedt et al. 2011).

The functional regions of the abovementioned arithmetic brain network, however, are not adjacent, but spatially distant from one another, which makes it crucial to study the structural white matter connections between these regions. This connectivity between brain regions is integral to efficient cognitive processing (Johansen-Berg 2010). Understanding the role of white matter pathways in arithmetic may thus further clarify the neural mechanisms of individual differences in arithmetic abilities (Matejko and Ansari 2015).

These white matter connections can be examined with diffusion-weighted magnetic resonance imaging (dMRI), an imaging technique that sensitizes the MRI signal to the diffusion (i.e., random molecular motion) of water molecules by adding diffusion encoding gradients in distinct directions to a standard MR pulse sequence (Jones and Leemans 2011). As yet, the simplest and most frequently applied model to relate the dMRI signal to the actual underlying neuroanatomy, is Diffusion Tensor Imaging (DTI). The classic DTI model estimates the degree to which diffusion is not spherical but increased in a certain direction (fractional anisotropy or FA) per voxel. The estimated direction of diffusion per voxel is then assumed to correspond to the dominant fiber orientation, and the estimated fractional anisotropy is assumed to correspond to the density, myelination and underlying architecture of the underlying axons (Basser et al. 1994; Tournier et al. 2007).

To date, structural connectivity within arithmetic has only been investigated through classic DTI, which is subject to methodological limitations. For example, DTI can only estimate the direction of one fiber per imaging voxel, which leads to an oversimplification of the underlying anatomy in regions with multiple crossing white matter fibers (Assaf et al. 2004; Tournier et al. 2007). As many of these crossing fibers are situated in and around the parietal lobe, results of the available DTI studies must be interpreted with caution. The current study is the first to tackle these issues in the field of arithmetic, by implementing a more novel and complex non-tensor model (i.e., spherical deconvolution), which, among other things, has the asset that it can characterize the orientation of more than one fiber per voxel, and consequently provides the possibility of making more accurate statements about the associations between white matter tracts and arithmetic fluency (Dell'Acqua et al. 2007; Tournier et al. 2004).

Despite the availability of these techniques, structural connectivity research in children's arithmetic is scarce and inconclusive, as many different white matter pathways have been found to be related to individual differences in arithmetic or other mathematical skills (see Matejko and Ansari 2015; Moeller et al. 2015 for reviews). For example, studies on children with atypical mathematical abilities (i.e., math-gifted children or children with developmental dyscalculia) point towards higher FA in several temporo-parietal regions for math-gifted children (ages 12–15), including the uncinate fasciculus (UF), superior longitudinal fasciculus (SLF), and inferior longitudinal fasciculus (ILF; Navas-Sánchez et al. 2014), or a significantly lower probability of connectivity to the right inferior temporal gyrus (i.e., the right ILF and inferior fronto-occipital fasciculus; IFOF) in children with mathematical difficulties (ages 7–9; Rykhlevskaia et al. 2009). A study by Kucian et al. (2014) also compared a group of children with dyscalculia to a group of age matched controls (ages 8–11), and found lower FA in parietal and insular white matter clusters. Even though these studies on children with atypical mathematical abilities provide insights into which white matter pathways are related to arithmetic performance, making generalizations to typically developing children about the neurocognitive processes at hand might be difficult.

Looking at typically developing children, a DTI study on individual differences in children's arithmetic by Van Eimeren et al. (2008) found a correlation between children's (ages 7–9) scores on the numerical operations subtest of the Wechsler individual achievement test (i.e., a test of written calculation including simple arithmetic problems of all operations) and FA in the left ILF and the left corona radiata (CR). The authors speculated that the ILF could be related to participants' processing efficiency of Arabic numerals, as inferior temporal brain regions, to which the ILF connects, were previously found to be important for visual representations of numerical symbols and calculation problems (Dehaene et al. 2003; Shum et al. 2013). The relation of this temporo-parietal connection to arithmetic fluency might also reflect verbal/memory representations of numbers, as they connect the fusiform regions with temporo-parietal white matter (Catani and Mesulam 2008). To a certain extent, these findings coincide with those of Rykhlevskaia et al. (2009), who found a correlation with the ILF in the right hemisphere, yet Van Eimeren et al. (2008) observed a correlation in the left hemisphere. These differences in hemisphere could be due to the atypical numerical processing in children with mathematical difficulties in Rykhlevskaia et al. (2009), yet, further research would be needed to clarify this. The left CR, on the other hand, had already been related to individual differences in reading skills (Ben-Shachar et al. 2007), which led Van Eimeren et al. (2008) to suggest that its involvement in mathematical processing could become co-opted for exact, verbal mathematical skills. However, as these projection fibers connect the thalamus with the sensorimotor cortex (Catani and Thiebaut de Schotten 2008), the notion of it having a role in perceptual and motor functions is more straightforward (Schmahmann and Pandya 2008).

A study by Tsang et al. (2009) used DTI tractography in 10- to 15-year-old children to investigate the relationship between fronto-parietal white matter and mathematical performance [i.e., the SLF and arcuate fasciculus (AF) connect frontal and parietal regions that are typically activated during arithmetic]. This was done by studying simple arithmetic facts, exact two-digit addition, and approximate two-digit addition. The study revealed an association between approximate addition and FA in the left anterior SLF, but not in the AF. However, remarks can be made on how both tracts were delineated. The AF needs to be divided into three different segments, which all connect different regions with one another and thus might have different functions (i.e., a direct, anterior and posterior segment, as proposed by Catani et al. 2005), and the SLF in its entirety contains three different parts as well (i.e., SLF I, SLF II, and SLF III; Thiebaut de Schotten et al. 2011). These distinctions were not made in Tsang et al. (2009), as the AF was considered a fronto-temporal part of the SLF. What was called the AF and SLF in the study by Tsang et al. (2009), however, seems to coincide with the direct and anterior segments of the AF, respectively, as discussed by Catani et al. (2005). A supplementary Tract-Based Spatial Statistics (TBSS) analysis in Tsang et al. (2009) also demonstrated correlations with approximate arithmetic beyond the left SLF/AF, including the bilateral SLF/AF, ILF, IFOF, CR, and corpus callosum (CC), thus suggesting that a broad network of white matter pathways is related to individual differences in children's arithmetic.

In a study by Van Beek et al. (2014), the critical segmentation of the AF into the three subcomponents was made, and an association was found between 12-year-old children's scores on addition and multiplication on a standardized timed arithmetic test (i.e., Tempo Test Arithmetic; De Vos 1992), and the FA of the anterior segment of the AF. However, the SLF as delineated by Tsang et al. and the anterior segment of the AF as delineated by Van Beek et al. coincide to a great extent. Historically speaking, the AF and the SLF have been thought to be the same tract, however, recently, attempts have been made to dissociate both tracts (e.g., Dick and Tremblay 2012; Zhao et al. 2016). This ambiguity in defining both the SLF and the AF especially becomes apparent in comparing these two studies, as it is thus presumable that they are dealing with the same tract; classic DTI analyses might not be fine-grained enough to properly disentangle both tracts (Zhao et al. 2016). To resolve such issues, more novel and complex non-tensor models (e.g., spherical deconvolution) are necessary to make accurate statements about the tracts' relevance to arithmetic performance. Either way, the existing studies seem to establish the importance of fronto- and temporo-parietal white matter pathways in children's arithmetic.

These available studies on white matter pathways in children's arithmetic, however, have some major shortcomings. To begin, all of them have analyzed the diffusion data by means of classic DTI, which is subject to various methodological limitations. First, DTI is unable to resolve the orientation of multiple crossing fibers within a voxel, as it can only estimate the direction of one fiber per imaging voxel. Consequently, this leads to an oversimplification or inaccurate representation of the underlying anatomy in regions with multiple crossing white matter fibers. Using DTI, the major eigenvector in voxels with crossing fibers generally does not correspond to the actual orientation of any of the fibers (Assaf et al. 2004; Tournier et al. 2007). This is highly problematic, as the percentage of white matter voxels that contain multiple crossing fibers in the human brain is around 70–90% (Dell'Acqua et al. 2013; Farquharson et al. 2013). As many of these crossing fibers are situated in and around the parietal lobe, which is a critical region for arithmetic, and even contains multiple smaller regions with distinct functions within arithmetic (e.g., intraparietal sulcus, angular gyrus, supramarginal gyrus; Arsalidou et al. 2018; Peters and De Smedt 2018), it is especially difficult to interpret the results from previous DTI studies on arithmetic, as tracts such as the SLF and AF that connect to these regions might have been difficult to disentangle with classic DTI.

Secondly, the interpretation of the FA index is not clear-cut, as it provides a quantitative measure per voxel that is determined by both microstructural (e.g., myelination of fibers, or size and density of cells) and macrostructural (e.g., number of crossing fibers) properties. A lot of anatomical information is thus reduced to just one index, implying that individual differences in FA could be due to a number of reasons, leading to difficulties in interpretation (Vanderauwera et al. 2015). Because of these shortcomings, results of previous DTI studies should be interpreted carefully, as they might not accurately reflect the associations between white matter tracts and arithmetic.

These two methodological limitations can be resolved using more complex non-tensor models, such as spherical deconvolution, which estimates a continuous 3D distribution of all possible fiber orientations within each voxel (Dell'Acqua et al. 2007; Tournier et al. 2004). Doing so, spherical deconvolution has the asset that it can characterize the orientation of more than one fiber per voxel, thus solving the crossing fibers problem. Furthermore, in comparison to other non-tensor models such as q-Ball imaging (Tuch 2004), diffusion spectrum imaging (Wedeen et al. 2005), and composite hindered and restricted model of diffusion (CHARMED; Assaf et al. 2004) imaging, which require the acquisition of higher or multiple *b* values and consequently demand extended scanning sessions, spherical deconvolution has an acquisition time close to DTI, and is therefore much more suited to use with children.

The advantages of spherical deconvolution have been clearly shown in a comparative study by Farquharson et al. (2013), who pointed out that, in voxels containing two fiber populations, spherical deconvolution properly identifies both fiber populations, while DTI does not provide an orientation estimate that corresponds to either of the populations. More specifically, in their study, DTI consistently failed to identify well-known corticospinal connections extending to the majority of the sensorimotor cortex, while spherical deconvolution produced the expected fan-shaped configuration of the corticospinal fiber pathways that much more closely resembles the known anatomy. Furthermore, to extract information on microscopic properties of the white matter tracts, the hindrance modulated orientational anisotropy (HMOA) index can be derived for quantitative spherical deconvolution analyses. This index can be defined as the absolute amplitude of each lobe of the fiber orientation distribution (Dell'Acqua et al. 2013). In contrast to FA, which provides a quantitative measure per voxel indexing both micro- and macroscopic properties, HMOA is a tract-specific index, highly sensitive to changes in fiber diffusivity (e.g., myelination processes or axonal loss) and to differences in the microstructural organization of white matter (e.g., axonal diameter and fiber dispersion). The index thus provides information about microscopic properties along each fiber orientation, even in regions with fiber crossings. Accordingly, the HMOA index can detect small changes in the microstructural properties along single white matter tracts, which are not detectable with classic DTI. By applying this tract-specific index, we might thus be able to detect fiber diffusivity changes (e.g., developmental myelination processes) and can improve tractography to better map white matter complexity inside the brain (Dell'Acqua et al. 2013). Against this background, spherical deconvolution is particularly suited to overcome the limitations associated with the classic tensor model.

Another problem in many of the existing DTI studies in children's arithmetic, is that data were collected from children with wide age ranges (e.g., 7–10 or 10–15 years old). The problem here is that this period in time is characterized by large structural white matter development (e.g., Barnea-Goraly et al. 2005), and that, consequently, although statistically controlled for, the observed correlations between individual differences in arithmetic and white matter might still be swayed by maturation, instead of being purely related to mathematical achievement. As mathematical achievement also improves over child development, high experience-dependent plasticity can be expected in white matter (e.g., Casey et al. 2006), which means that homogenous age groups (i.e., research samples with a small age range) should be studied to take such maturation effects into account.

To the best of our knowledge, the current study is the first to use spherical deconvolution to investigate which white matter tracts are related to differences in children's arithmetic fluency. We will also focus on children with a small chronological age range to minimize confounds of maturation. In addition, we not only implemented frequentist, but also Bayesian statistics for data analyses, as Bayesian statistics have the advantage of being able to quantify the evidence that the data provide for one hypothesis over another (Andraszewicz et al. 2015). In contrast to classic frequentist hypothesis testing, these Bayesian statistics are particularly informative when no association is observed, as they can quantify the evidence in favor of the null hypothesis of no association. These statistics are also not affected by the multiple comparison problem (Dienes 2011). In light of the above-reviewed DTI literature, we expect to find relations between arithmetic fluency and the white matter integrity of the SLF/AF, and ILF.

Methods

Participants

The study started with 50 typically developing Flemish 4th graders, yet due to technical acquisition problems ($n = 1$), excessive motion ($n = 1$), or problems during standardized testing ($n = 1$), data of 3 children were discarded. The remaining 47 participants (ages 9–10; $M = 9.68$, SD 0.33; 26 boys, 21 girls; 8 left-handed) had no history of learning difficulties, or neurological or psychiatric disorders. All children were recruited via the elementary school they attended, in the vicinity of our university, and were given a financial compensation in return for participating. Written informed consent was obtained from a parent or legal guardian of each participating child. The study was approved by the Medical Ethical Committee of the University of Leuven (S59167).

All participants took part in two test sessions. During the first session, behavioral data were collected through standardized measures. This session always preceded the second session by 2–3 weeks ($M = 19.54$ days, SD 6.34), which included the acquisition of the MRI data. This MRI acquisition session also partly contained fMRI data collection for another study, which is reported in Polspoel et al. (2017).

Standardized assessment

The standardized assessment session consisted of the evaluation of arithmetic, as well as intelligence, motor reaction time, and reading. First of all, the Tempo Test Arithmetic (TTA; de Vos 1992) was used to measure the children's arithmetic competence. This is a standardized test of arithmetical fluency, similar to the Math Fluency subtest of the Woodcock–Johnson III tests of achievement (Woodcock et al. 2003), and is very sensitive to individual differences in arithmetic fluency. The TTA is constructed of five columns of arithmetic items of increasing difficulty (i.e., one column per operation and a fifth column with mixed operations; each column starts with single-digit items), for which each child gets 1 min per column to write down as many correct answers as possible. Next, intellectual ability was measured by the WISC-III-NL Block Design and Vocabulary subtests, as measures of performance and verbal IQ respectively (Wechsler 2005). To measure motor reaction time, two figures (always a circle, triangle, square, star, or heart) were presented on a computer screen. Each participant had to indicate which of both figures (i.e., left or right) was filled in white, by, as quickly as possible, pressing the corresponding key. Accuracy and reaction time were recorded for each trial (De Smedt and Boets 2010). Finally, we measured the children's reading ability to investigate the specificity of our results (i.e., in comparison with a different symbolic academic skill). Reading ability was assessed using a combination of the one-minute test (OMT; Brus and Voeten 1979) and the Klepel (Van den Bos et al. 1994), which measure the reading of words and pseudowords, respectively; both tests consist of 116 words. For the OMT, the children get 1 min to correctly read aloud as many words as possible; for the Klepel, the time limit is set to 2 min, and the children read aloud pseudowords. Other behavioral measures, such as strategy assessment, or sensitivity-to-interference, were also assessed in sub-samples of this study, but not reported here as they were linked to fMRI protocols of different studies (Polspoel et al. 2017).

MRI data acquisition and tractography

MRI scanning was done with a Philips Ingenia 3.0 T CX MRI scanner with a SENSE 32-channel head-coil, located at the Department of Radiology of the University Hospital in Leuven, Belgium. Wash cloths were used to stabilize the children's heads and consequently minimize head motion. dMRI sagittal slices were obtained using the following parameters: 60 noncollinear directions *b* value 2000 s/mm^2, 30 noncollinear directions *b* value 700 s/mm^2 (which were eventually discarded for spherical deconvolution analyses), 6 nondiffusion-weighted images, 2.5 × 2.5 × 2.5 mm voxel size, 90° flip angle, repetition time (TR) 7000 ms, echo time (TE) 72 ms, and 240 × 125 × 240 mm field of view (approximately 12 min of scanning time). Anatomical T1 images were acquired with the following sequence: 0.98 × 0.98 × 1.2 mm voxel size, 256 × 256 acquisition matrix, 8° flip angle, TE 4.6 ms, 250 × 250 × 218 mm field of view (approximately 8 min of scanning time). As a part of data collection for different studies (Polspoel et al. 2017), the scanning session also included four fMRI runs of approximately 5 min, leading to a total scanning time of approximately 40 min.

All pre-processing was done using the Explore DTI software (Leemans et al. 2009), and existed of visual quality assurance, and rigorous motion, eddy current-induced distortion, and EPI distortion correction. After motion correction, data of participants which displayed excessive motion ($n = 1$), defined as a mean translation in any direction greater than the voxel size of 2.5 mm, were discarded. No normalization to a standard atlas took place. Whole-brain DTI tractography was performed with FA-threshold = 0.20, maximum turning angle = 30°, and step length between calculations = 1 mm. For the spherical deconvolution analyses, additional processing was done with the StarTrack software (Dell'Acqua et al. 2013), using the following parameters: iterations = 200, $n = 0.04$, and $r = 8$. Finally, the following parameters were used for the spherical deconvolution whole-brain tractography: absolute HMOA threshold = 0.06, relative HMOA threshold = 5%, maximum turning angle = 30°, and step length between calculations = 1 mm.

Tractography of the white matter tracts was performed with the TrackVis software (Wang et al. 2007). All tracts were manually delineated for each subject using a region of interest (ROI) approach, based on anatomical landmarks in color-coded maps (Catani and Thiebaut de Schotten 2008; Thiebaut de Schotten et al. 2011; Wakana et al. 2007). In this approach, each ROI represents an obligatory passage for the tract at hand. The colors in these maps refer to the direction the fibers run in; red are commissural fibers, green are associative fibers, and blue are projection fibers.

The white matter pathways that were investigated in the current study were based on the existing literature (Matejko and Ansari 2015), as well as the ROIs used to perform the manual segmentation of each tract (Catani and Thiebaut de Schotten 2008; Thiebaut de Schotten et al. 2011; Wakana et al. 2007). An overview of the connections of each tract and the ROIs used for delineation, can be found in Table 1. The same ROIs were used for both the spherical deconvolution and DTI delineations, to maximize the comparability of the HMOA and FA metrics, respectively. A visual overview of the tracts under study, delineated with spherical deconvolution, can be found in Fig. 1. For comparison, the same tracts for the same participant, but delineated with classic DTI, can be found in Appendix Fig. 1.

After manually delineating a white matter pathway, the TrackVis software offers statistical information of the tract at hand (e.g., HMOA value, amount of fibers, volume, etc.), which can then be used for statistical testing.

Table 1 Overview of connections and regions of interest (ROI) for each tract under study

Tract	Connections	ROIs
Inferior fronto-occipital fasciculus	Occipital cortex to frontal lobe, through deep temporo-basal areas and insula (Martino et al. 2010)	ROI 1: coronal slice at anterior edge of the genu ROI 2: occipital lobe on coronal slice at middle point between posterior edge of the cingulum and posterior edge of parieto-occipital fissure
Inferior longitudinal fasciculus	Occipital lobe to anterior part of temporal lobe, including fusiform gyri and parahippocampal regions (Catani et al. 2005)	ROI 1: coronal slice at posterior edge of cingulum ROI 2: entire temporal lobe at most posterior coronal slice where temporal lobe is separated from frontal lobe
Arcuate fasciculus	Perisylvian regions of frontal, parietal, and temporal lobes with each other—separated into a direct segment (ROIs 1 and 3), an anterior segment (ROIs 1 and 2, without 3) and a posterior segment (ROIs 3 and 4, without 1) (Catani et al. 2005)	ROI 1: arch-shaped dorsal ROI on coronal slice at middle of posterior limb of internal capsule ROI 2: association fibers on coronal slice at middle of splenium ROI 3: lateral posterior ROI on axial slice at level of anterior commissure ROI 4: lateral posterior ROI on axial slice, similar to ROI 3, yet 5–7 slices more superior
Superior longitudinal fasciculus	Large parieto-frontal connections, separated into a dorsal superior (SLF1; ROIs 1 and 2), middle (SLF2; ROIs 1 and 3), and ventral part (SLF3; ROIs 1 and 4) (Thiebaut de Schotten et al. 2011)	ROI 1: entire parietal lobe on coronal slice at level of posterior commissure ROI 2: superior frontal gyrus on coronal slice at level of anterior commissure ROI 3: middle frontal gyrus on coronal slice at level of anterior commissure ROI 4: precentral gyrus on coronal slice at level of anterior commissure
Uncinate fasciculus	Lateral orbitofrontal cortex to anterior temporal lobe (Von Der Heide et al. 2013)	ROI 1: entire temporal lobe at most posterior coronal slice where temporal lobe is separated from frontal lobe ROI 2: all projections towards frontal lobe in the same slice as ROI 1
Corona radiata and corticospinal tract	Projection fibers, carrying neural traffic to and from cerebral cortex (CST—specifically to and from primary motor cortex) (Han et al. 2010)	ROI 1: entire cerebral peduncle on axial level of decussation of superior cerebellar peduncle ROI 2 (CST): ROI around bundle of trajectories that reach primary motor cortex
Corpus callosum	Largest of commissural fibers, linking cerebral cortex of left and right hemisphere (Wakana et al. 2007)	Forceps major ROI 1 & 2: coronal slice at most posterior edge of parieto-occipital fissure (bilaterally) Forceps minor ROI 1 & 2: coronal slice in the middle of anterior edge of frontal cortex and genu (bilaterally)

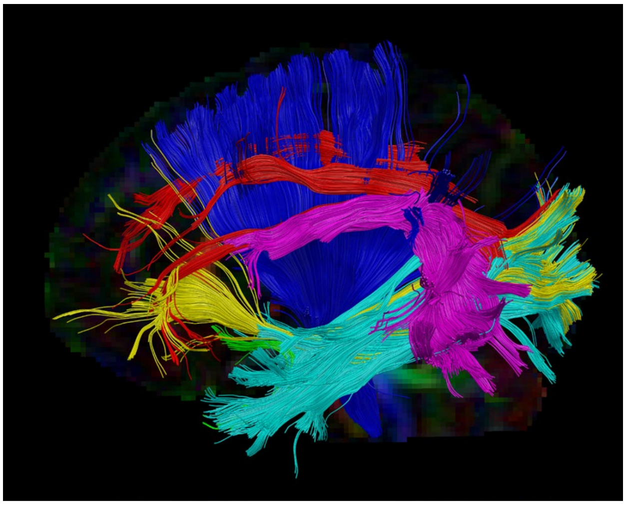

Fig. 1 Overview of the white matter pathways under study, delineated with spherical deconvolution: in red the SLF I, SLF II, and SLF III; in fuchsia the AF; in yellow the IFOF; in cyan the ILF; in green the UF; in blue the CR. For purpose of clarity, the corpus callosum is not depicted in this image, yet it was also under study

Statistical analyses

All statistical analyses were performed with the JASP software package (JASP Team 2017). We calculated Pearson correlations between the results of the TTA (i.e., of all columns separately and of the total score) and the HMOA values of all tracts under study, and their corresponding Bayes Factors. Since our sample had a small age range, and all participants were part of the same norm group, raw scores of the TTA (i.e., number of correctly solved items within 1 min) were used for the correlation analyses. Only tracts with a minimum of 20 fibers were used for data analyses. The Bayesian approach was implemented, as it has the advantage to quantify the evidence that data provide for one hypothesis over another (Andraszewicz et al. 2015). Accordingly, Bayes factors (BF_{10}) of 1, 1–3, 3–10, 10–30, 30–100, or > 100 respectively point towards no, anecdotal, substantial, strong, very strong, or decisive evidence for the alternative hypothesis (Jeffreys 1961). Additionally, Bayesian analyses allow us to verify the extent to which the data are in favor of the null hypothesis of no association (i.e., Bayes factors of 1–1/3, 1/3–1/10, 1/10–1/30, 1/30–1/100, < 1/100 respectively point towards anecdotal, substantial, strong, very strong, or decisive evidence for the null hypothesis; Jeffreys 1961). These statistics are also not affected by the multiple comparison problem (Dienes 2011). Results of frequentist approaches to statistical testing are also reported, implementing the Bonferroni method of controlling for multiple comparisons (p = target alpha level/number of delineated tracts; $p = 0.05/25 = 0.002$). To control for other variables such as IQ, and motor reaction time, partial correlations were calculated with IQ and motor reaction time simultaneously added as control variables. Correlations were also calculated with our reading measure as to assure that any observed associations between the tracts and arithmetic fluency, are not observed with another symbolic skill, measured in a similar (i.e., time-limited) way, thus testing the specificity of the results. For the sake of comparison, all analyses were also conducted with the FA values when implementing classic DTI to analyze the neural data.

Results

Behavioral results

Figure 2 displays box plots with the descriptive statistics of arithmetic, intellectual ability, motor reaction time, and reading. The means of our sample were close to the expected population averages, and show proper variation. An important note is that even though the minimum score for some of the tasks was low, none of the participating children had been diagnosed with any type of learning disorder or intellectual disability.

Correlations with white matter integrity

Pearson correlations, using both Bayesian and frequentist approaches, were calculated between the HMOA values of the various tracts and participants' scores on the TTA. Table 2 summarizes the main results of the spherical deconvolution analyses and presents positive correlations for which we observed at least substantial evidence in favor of the hypothesis of an association between HMOA of a given tract and individual differences in TTA ($BF_{10} > 3$; see Jeffreys 1961 for an interpretation of Bayes Factors), and for which a significant correlation using frequentist statistics ($p < 0.05$) was found.

Correlations were found between the HMOA values of the right ILF and arithmetic performance across all operations. The Bayesian analyses indicated that the evidence for these associations was strong for addition and multiplication, very strong for division, and decisive for subtraction, the mixed column and the total score of the TTA. Using the frequentist approach, all correlations, except for addition, remained significant when using a Bonferroni method of controlling for multiple comparisons. The results also remained significant when simultaneously controlling for IQ, and motor reaction time. We also observed an association between the HMOA values of the right UF and subtraction, for which the evidence was substantial. Using the frequentist approach, significant correlations were also found for division, the mixed column and the total score of the TTA. These significant correlations, however, did not survive a Bonferroni method

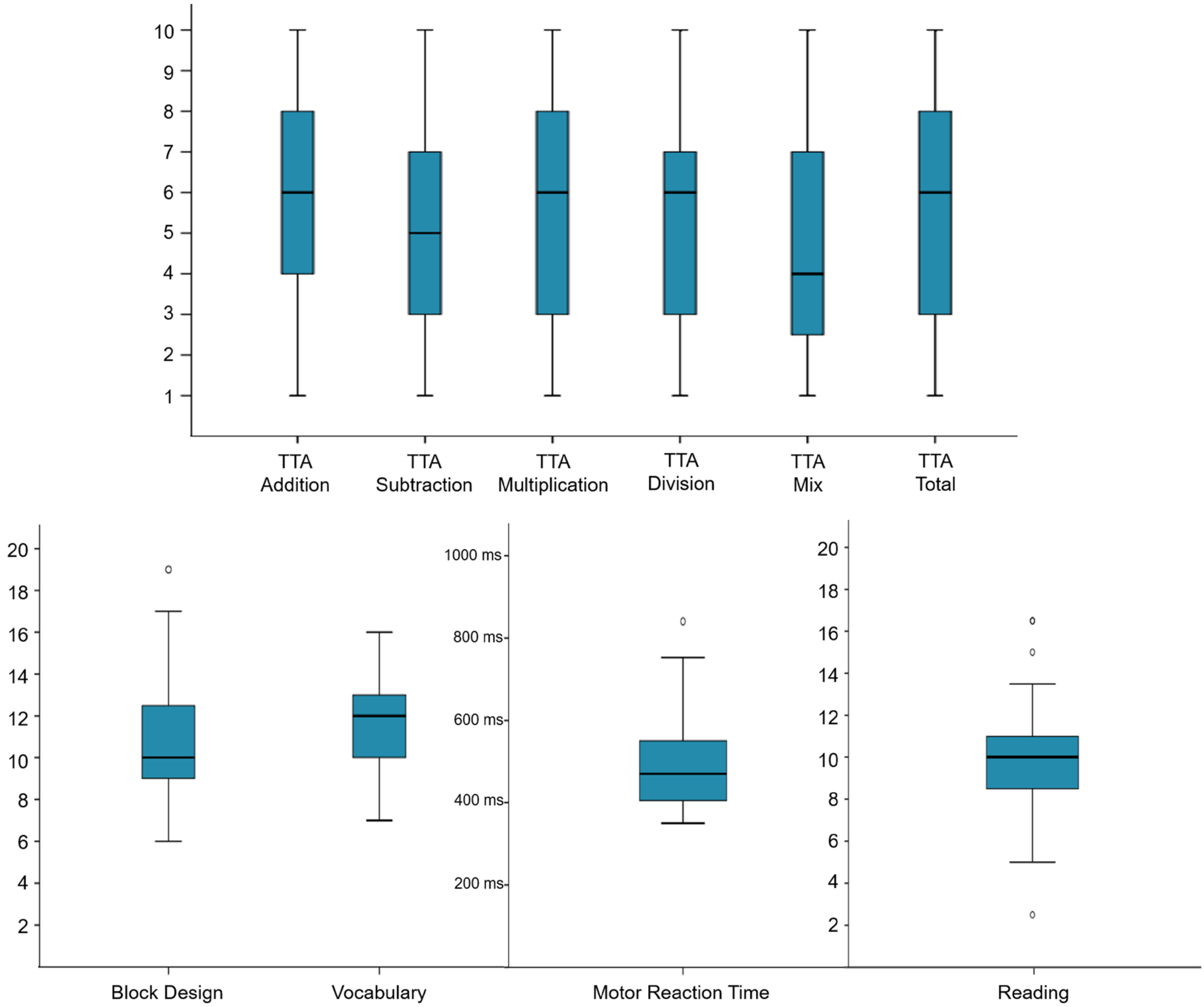

Fig. 2 Box plots displaying performance on arithmetic, intellectual ability, motor reaction time, and reading. The scores for arithmetic, intellectual ability, and reading are standardized scores. The scores on the arithmetic test are standardized as $M=5$, SD 2, with a maximum of 10. The scores on the intelligence and reading tests are standardized as $M=10$, SD 3, with a maximum of 19. The scores for motor reaction time are raw scores displaying the average reaction time

of controlling for multiple comparisons. The correlation for subtraction was also the only one that remained significant when controlling for IQ and motor reaction time.

Visual representations of the right ILF and right UF can be found in Fig. 3. Scatterplots with linear fit lines of the associations between the HMOA values of these tracts and performance can be found in Fig. 4. To test the specificity of these results to arithmetic fluency, we checked whether these associations could also be observed with a different symbolic measure (i.e., reading, calculated as the average score on both OMT and Klepel tests). This was not the case, as no significant correlations were observed between reading with either the right ILF ($r=0.213$; $p=0.075$; $BF_{10}=0.914$) or right UF ($r=0.183$; $p=0.109$; $BF_{10}=0.673$).

No evidence was found for associations between scores on the TTA and the HMOA values of any of the segments of either SLF or AF, even though this was hypothesized based on the available literature. The Bayes factors (BF_{10}) for almost all of these correlations were below 1, indicating that the null hypothesis of no association between arithmetic fluency and these tracts is more likely than the existence of an association. This evidence for the null hypothesis, however, was not substantial (i.e., $BF_{10}<1/3$) across all segments and operations, but was often anecdotal (i.e., $1<BF_{10}<1/3$; Jeffreys 1961; see Appendix Table 1 for a more detailed overview).

Finally, the associations between the tracts under study and individual differences in arithmetic fluency were also

Table 2 Correlations between the HMOA (spherical deconvolution) and FA (DTI) values of the right ILF and right UF, and participants' scores on the TTA for each operation and in total

	TTA addition		TTA subtraction		TTA multiplication		TTA division		TTA mix		TTA total	
	HMOA	FA	HMOA	FA	HMOA	FA	HMOA	FA	HMOA	FA	HMOA	FA
Right ILF												
Pearson's r	0.395	0.249	0.570	0.451	0.423	0.370	0.430	0.252	0.481	0.404	0.528	0.391
BF_{10}	14.25	1.37	1771.5	49.21	25.63	8.62	30.04	1.42	105.52	16.9	414.11	13.1
p value	0.003	0.046	< 0.001	< 0.001	0.002	0.005	0.001	0.044	< 0.001	0.002	< 0.001	0.003
Right UF												
Pearson's r	0.096	−0.008	0.353	0.274	0.063	0.076	0.255	0.233	0.277	0.249	0.254	0.204
BF_{10}	0.327	0.174	6.419	1.902	0.261	0.285	1.476	1.144	1.971	1.370	1.468	0.830
p value	0.260	0.523	0.007	0.031	0.337	0.305	0.042	0.057	0.030	0.046	0.042	0.084

The Bayes factors (BF_{10}) report the amount of evidence found for a positive association between the tracts and the TTA. Such evidence is considered substantial, strong, very strong, or decisive for the alternate hypothesis if the Bayes factor is above 3, 10, 30, or 100, respectively, or for the null hypothesis if the Bayes factor is below 1/3, 1/10, 1/30, or 1/100, respectively

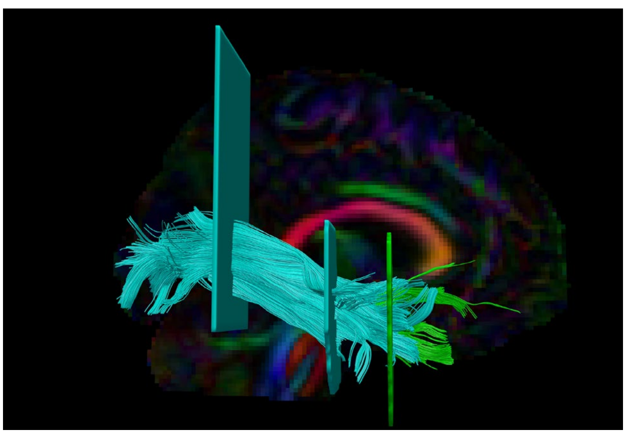

Fig. 3 Visual representations of the white matter tracts found to be associated with individual differences in arithmetic fluency. Cyan: right-hemispheric ILF delineated on a color-coded map; the ILF is delineated by an entire coronal slice at the posterior edge of the cingulum, and an ROI entailing the entire temporal lobe on the most posterior coronal slice in which the temporal lobe is not connected to the frontal lobe. Green: right-hemispheric UF; the UF is delineated by an ROI on the entire temporal lobe at the most posterior coronal slice where the temporal lobe is separated from the frontal lobe, and a second ROI that includes all projections towards the frontal lobe in the same slice as the first ROI

analyzed using classic DTI metrics (i.e., the FA index). These analyses yielded similar results for the right ILF (see Table 2). The spherical deconvolution analyses, being more specific to white matter properties, also displayed stronger associations between arithmetic fluency and the right ILF than the DTI analyses. With DTI, only anecdotal evidence was found for associations between FA and addition and division for the right ILF. Using the frequentist approach, significant results were found across operations, yet only the results for subtraction survived controlling for multiple comparisons. For the right UF, which did display significant associations with arithmetic fluency when using spherical deconvolution, only anecdotal evidence was found when using classic DTI. Significant p values were observed for the associations between FA and subtraction and the mixed column, yet these results did not survive when controlling for multiple comparisons. All significant correlations, however, stayed significant when simultaneously controlling for IQ and motor reaction time. As with the spherical deconvolution analyses, no evidence for an association with any of the other tracts was found. Furthermore, using classic DTI, parts of the SLF were only traceable in 5 out of 47 participants, due crossing fibers with either CR, AF, or corpus callosum. This made it impossible to examine the correlations between FA in the SLF and arithmetic (Appendix Table 1).

Discussion

When it comes to arithmetic fluency, contemporary DTI research points to a variety of tracts (i.e., the AF, SLF, ILF, IFOF, UF, and others) as being related to children's arithmetic performance (Matejko and Ansari 2015). However, the existing studies all applied classic DTI to study various white matter tracts, a method which is subject to methodological limitations (e.g., Assaf et al. 2004; Dell'Acqua et al. 2013; Farquharson et al. 2013; Tournier et al. 2007) such as the fact that DTI can only estimate the direction of one fiber per imaging voxel, leading to an oversimplification or inaccurate representation of the underlying anatomy. Furthermore, these studies were all conducted in research samples with wide age ranges (e.g., 7–10 or 10–15 years old; Matejko and Ansari 2015), which, even though statistically controlled for, might lead to maturational confounds and consequently to the over-interpretation of associations

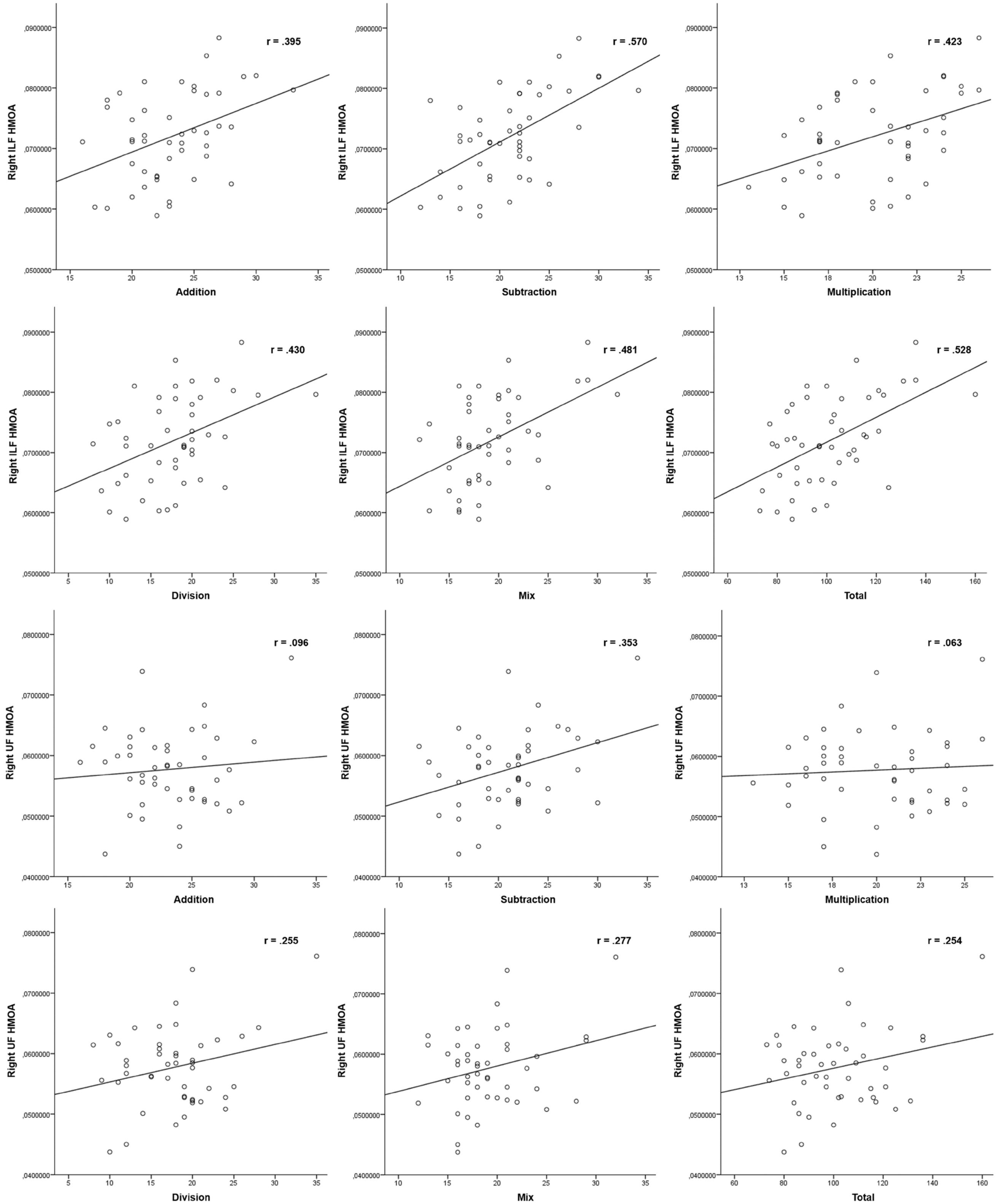

Fig. 4 Scatterplots with fit lines of the associations between all the columns and the total score of the TTA, and the HMOA values of the right ILF and right UF

between differences in connectivity and differences in mathematical development. As a result, not that much is known about the actual relation between structural white matter tracts and children's arithmetic. These limitations, however, can be tackled by implementing spherical deconvolution, which can characterize the orientation of more than one fiber per voxel, and from which the HMOA index, which is tract-specific and provides information about the diffusion properties along each fiber orientation (Dell'Acqua et al. 2013), can be derived. The current study was the first to implement spherical deconvolution to investigate the associations of white matter tracts and individual differences in typically developing children's arithmetic fluency, and focused on children with a small age range (9- to 10-year-olds), as to minimize confounds of maturation.

Our results primarily point towards an association of the right ILF and individual differences in children's arithmetic fluency. The current findings echo previous results with classic DTI in which associations between FA in the ILF and individual differences in mathematics have been observed (Li et al. 2013; Navas-Sánchez et al. 2014; Rykhlevskaia et al. 2009; Van Eimeren et al. 2008). For example, correlations were found between FA in the left ILF and the arithmetic subtest of the WISC in 9–11-year-olds (Li et al. 2013) and the numerical operations subtest of the WIAT in 7–9-year-olds (Van Eimeren et al. 2008), albeit in the left hemisphere instead of the right. Furthermore, group differences were found in the FA of the bilateral ILF between controls and math-gifted children, with math-gifted children having higher FA values (Navas-Sánchez et al. 2014) and in the right ILF between controls and children with dyscalculia, with the control group having higher FA values (Rykhlevskaia et al. 2009). The current study in typically developing children thus found similar results, as correlations were found between the white matter integrity of the ILF and children's arithmetic fluency. Our findings, however, go beyond the existing literature, by focusing on a narrow age range, and by implementing a more reliable method of analyzing the diffusion data (i.e., spherical deconvolution, with the associated HMOA index).

What could this association between the ILF and arithmetic fluency potentially reflect? The ILF connects the occipital lobe to the anterior part of temporal lobe, including the fusiform gyri and parahippocampal regions. In arithmetic, this tract might be related to the efficiency with which children process Arabic numerals, as research has shown that inferior temporal regions are involved in the processing of visual representations of numerical symbols (Dehaene et al. 2003; Shum et al. 2013). More recently, increased activation in the inferior temporal gyrus has even been observed to be driven by broader mathematical processing, instead of a specific preference to Arabic numbers (Grotheer et al. 2018), which might also explain the ILF's relevance within arithmetic. The ILF also mediates the interaction between medial, inferior and anterior temporal cortices with Perisylvian areas, and is thus related to language (Catani and Mesulam 2008). As such, it is possible that the ILF is important for exact verbal arithmetic skills (e.g., fact retrieval), as it could subserve as a first step in connecting the lingual, fusiform, and parahippocampal regions in the ventral visual stream, upwards to the dorsal visual stream and thus, possibly via other tracts such as the AF or SLF, eventually to the IPS and superior parietal lobe (Rykhlevskaia et al. 2009). Furthermore, recent fMRI research in children has indicated middle temporal regions as being increasingly activated during fact retrieval, and thus for fast automated processes (Polspoel et al. 2017). These mid-temporal regions coincide with the anatomical location of the ILF. The function of the ILF could thus go beyond fluency in processing numerical symbols, but it may also be relevant for general arithmetic fluency. Further research is thus needed to define the exact role of the ILF within arithmetic fluency.

Correlations were also found between arithmetic—yet mainly in subtraction—and the HMOA values of the right UF. This result concurs with previous research, in which increased FA in the right UF was observed when using TBSS to compare math-gifted children to controls (ages 12–15; Navas-Sánchez et al. 2014). The exact function of the UF within arithmetic, however, is still unclear. The main role of the UF, which connects the lateral orbitofrontal cortex with the anterior temporal lobes, seems to lie within temporal lobe-based mnemonic associations (Von Der Heide et al. 2013). As such, the UF could have an assisting role within memory, which could also explain the tract's role within arithmetic. Recently, a meta-analysis in children's arithmetic also highlighted the importance of the right insular cortex (i.e., a locus of the right UF) within calculation (Arsalidou et al. 2018), thus supporting the possibility of importance for this tract within children's arithmetic. A recent fMRI study on the neural differences between fact retrieval and procedural strategy use even points towards relevance for temporal regions and the orbitofrontal cortex during fact retrieval (Polspoel et al. 2017). It is thus plausible that the UF maintains this connection and is consequently important for more automated processes within arithmetic. The association between UF and individual differences in arithmetic, on the other hand, needs to be interpreted with caution, as the Bayesian analyses indicated that the evidence for this association was mainly anecdotal.

It is important to point out that none of the other previously found associations between white matter tracts (i.e., CC, CR, CST, AF, SLF, or IFOF; Matejko and Ansari 2015) and mathematical abilities were found in the present study. The Bayesian statistics implemented in the current study even pointed to towards, albeit not always substantial, evidence for the null hypothesis of no association between arithmetic and the AF and SLF, even though these tracts were found to be related to children's arithmetic in previous studies (e.g., Tsang et al. 2009; Van Beek et al. 2014).

The absence of associations with these tracts in our results can be explained by various factors. First, in contrast to the current study in which we tried to minimize confounds of maturation, the available studies have been conducted in typically developing samples of children with wider age ranges than those of the current study (e.g., 7–9 years old; Van Eimeren et al. 2008; 10–15 years old; Tsang et al. 2009), leaving it unresolved to which extent found associations are due to maturation or to actual individual differences in performance. Second, the absence of a correlation with some of the previously observed tracts in the current study might also be due to the specificity of the tasks under study. The current study used results on the TTA (i.e., a timed arithmetic task based on fluency, with basic arithmetic items across all operations) for correlations with white matter indices. Some of the previous studies, however, did not focus on arithmetic fluency, but implemented a broader and/or untimed assessment of mathematical abilities. For example, Van Eimeren et al. (2008) assessed mathematics through the numerical operations and mathematical reasoning subtests of the WIAT-II, and in Navas-Sánchez et al. (2014), the math-gifted children were selected based on their enrolment in a program for mathematically talented children, and not on their arithmetic skills. This could also explain differences in results, as the tracts found in the current study might be specific to arithmetic fluency, but might not be found for individual differences in other mathematical skills, such as mathematical reasoning. Finally, all of the existing dMRI literature in the field of arithmetic has implemented classic DTI, which, as mentioned, has some methodological constraints (Assaf et al. 2004; Dell'Acqua et al. 2013; Farquharson et al. 2013; Tournier et al. 2007). Even though, as the results of the current study point out, DTI and spherical deconvolution analyses lead to similar results, the spherical deconvolution analyses are more accurate and provide stronger results. Consequently, it is possible that, in combination with a wider age range and with the use of different mathematical tasks, the use of classic DTI in previous studies might have led to the analyses not being powerful enough to consistently detect relationships with the right ILF, or to observing relationships with other tracts such as the AF or SLF.

The associations of the right ILF with arithmetic fluency were also observed across operations, even though in previous research, neural differences between operations have been observed, both functionally (e.g., De Smedt et al. 2011; Prado et al. 2011) and structurally (Van Beek et al. 2014). These neural differences, however, were most likely due to differences in the arithmetic strategies used to solve items of a certain operation (Polspoel et al. 2017; Prado et al. 2011). As the TTA largely consists out of single-digit items, the likelihood of a fact retrieval strategy in the children under study occurring across all operations was large, which might explain the fact that no clear operation differences were observed. However, our measure of arithmetic did not allow us to analyze the used strategies for each operation, as the problems were not selected to specifically elicit one strategy or the other, and we did not ask children to report on their strategy use, thus making it hard to form conclusions on this issue. We contend that future research should implement more carefully designed tests of each operation (i.e., targeting particular strategies) or the collection of strategy data through verbal self-reports as an alternative avenue. Such research might also aid in clearly defining the role of the ILF within arithmetic.

In line with previous research (e.g., Farquharson et al. 2013), the current study shines light on dMRI research that goes beyond classic DTI, and implements more complex non-tensor models such as spherical deconvolution when studying arithmetic ability. Furthermore, it needs mentioning that the existing studies on white matter involvement in children's arithmetic often collected data from children with wide age ranges (e.g., 7–10 or 10–15 years old; Matejko and Ansari 2015), which is a time period characterized by large white matter development (e.g., Barnea-Goraly et al. 2005). Consequently, merging data across wide age ranges, even though statistically controlled for, might lead to the over-interpretation of associations between differences in connectivity and differences in mathematical development, as results might still be affected by maturational confounds. To take this problem into account, the current study was conducted with a research sample of only 9–10-year-olds (i.e., fourth graders). Accordingly, it is crucial to emphasize the need for similar studies in children of different ages, such as first or second graders (i.e., children who are at the beginning of their arithmetic development) or children in secondary school. Studies with a longitudinal follow-up throughout development are also deemed necessary.

It is also important to emphasize that learning arithmetic does not occur in isolation, but that it is highly dependent on the general educational environment in which these skills evolve, as well as the emphasis on automatization processes within the mathematics curriculum (De Smedt 2016). For example, a comparison of the fact retrieval frequencies in single-digit addition and subtraction in American (Geary et al. 2004) and Belgian (Torbeyns et al. 2004) third-graders revealed a relative retrieval frequency of 38% and 88%, respectively. As all participants of the current study came from Belgian elementary schools, high automatization skills were to be expected. In accordance, it is plausible that studies across cultures with differences in the emphasis on such fast automated processes might point towards the involvement of different white matter tracts for the same set of arithmetic items as were found in our sample.

Finally, we would like to emphasize the necessity of similar research, not just across age groups or different cultures, but in atypical populations, such as math-gifted children, or children with developmental dyscalculia, as this could deliver additional insights into the neural development of these mathematical skills.

Alongside the abovementioned existing studies, the current study implemented a structural approach to connectivity (i.e., dMRI), leaving the possibility open of studying connections between neural regions involved in children's arithmetic in a functional manner. Functional connectivity analyses use fMRI to study consistent signal changes in anatomically distant regions, yet only a very limited number of such studies exist within arithmetic (Peters and De Smedt 2018). In all, we feel that these suggestions yield the possibility of providing a fruitful contribution to the emerging field of educational neuroscience.

Acknowledgements This study was supported by a project of the Fund for Scientific Research Flanders (G.0946.12), by a federal research action (IUAP P7/11), and by a project of the Fund for Scientific Research Flanders and the Austrian Science Fund (G.0027.16). We would also like to thank all participants, their parents, and the Department of Radiology of the University Hospital in Leuven for their support.

Funding This study was funded by a project of the Fund for Scientific Research Flanders (G.0946.12), by a Belgian federal research action (IUAP P7/11), and by a project of the Fund for Scientific Research Flanders and the Austrian Science Fund (G.0027.16).

Compliance with ethical standards

Informed consent Written informed consent was obtained from all individual participants included in the study, as well as from a parent or legal guardian of each participating child.

Ethical approval All procedures involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. The study was approved by the Medical Ethical Committee of the University of Leuven (S59167).

Conflict of interest The authors declare that they have no conflict of interest.

References

Andraszewicz S, Scheibehenne B, Rieskamp J, Grasman R, Verhagen J, Wagenmakers EJ (2015) An introduction to Bayesian hypothesis testing for management research. J Manag 41:521–543

Arsalidou M, Taylor MJ (2011) Is 2 + 2 = 4? Meta-analyses of brain areas needed for numbers and calculations. Neuroimage 54:2328–2393

Arsalidou M, Pawliw-Levac M, Sadeghi M, Pascual-Leone J (2018) Brain areas associated with numbers and calculations in children: meta-analyses of fMRI studies. Dev Cogn Neurosci 30:239–250

Assaf Y, Freidlin RZ, Rohde GK, Basser PJ (2004) New modeling and experimental framework to characterize hindered and restricted water diffusion in brain white matter. Magn Reson Med 52:965–978

Barnea-Goraly N, Menon V, Eckert M, Tamm L, Bammer R, Karchemskiy A, Reiss AL (2005) White matter development during childhood and adolescence: a cross-sectional diffusion tensor imaging study. Cereb Cortex 15:1848–1854

Basser PJ, Mattiello J, LeBihan D (1994) MR diffusion tensor spectroscopy and imaging. Biophys J 66:226–259

Ben-Shachar M, Dougherty RF, Wandell BA (2007) White matter pathways in reading. Curr Opin Neurobiol 17:258–270

Brus BT, Voeten MJM (1979) Een Minuut Test (one minute test). Swets & Zeitlinger, Lisse

Casey BJ, Tottenham N, Limston C, Durston S (2006) Imaging the developing brain: what we have learned about cognitive development. Trends Cogn Sci 9:104–110

Catani M, Mesulam M (2008) The arcuate fasciculus and the disconnection theme in language and aphasia: history and current state. Cortex 44:953–961

Catani M, Thiebaut de Schotten M (2008) A diffusion tensor imaging tractography atlas for virtual in vivo dissections. Cortex 44:1105–1132

Catani M, Jones DK, ffytche DH (2005) Perisylvian language networks of the human brain. Ann Neurol 57:8–16

De Vos T (1992) Tempo-Test-Rekenen. Berkhout, Nijmegen

De Smedt B (2016) Individual differences in arithmetic fact retrieval. In: Berch D, Geary D, Mann-Koepke K (eds) Development of mathematical cognition: Neural substrates and genetic influences, vol 2. Elsevier, San Diego, pp 219–243

De Smedt B, Boets B (2010) Phonological processing and arithmetic fact retrieval: evidence from developmental dyslexia. Neuropsychologia 48:3973–3981

De Smedt B, Holloway ID, Ansari D (2011) Effects of problem size and arithmetic operation on brain activation during calculation in children with varying levels of arithmetical fluency. Neuroimage 57:771–781

Dehaene S, Piazza M, Pinel P, Cohen L (2003) Three parietal circuits for number processing. Cogn Neuropsychol 20:487–506

Dell'Acqua F, Rizzo G, Scifo P, Clarke RA, Scotti G, Fazio F (2007) A model-based deconvolution approach to solve fibercrossing in diffusion-weighted MR imaging. IEEE T Biomed Eng 54:462–472

Dell'Acqua F, Simmons A, Williams SCR, Catani M (2013) Can spherical deconvolution provide more information than fiber orientations? Hindrance modulated orientational anisotropy, a true-tract specific index to characterize white matter diffusion. Hum Brain Mapp 34:2464–2483

Dick AS, Tremblay P (2012) Beyond the arcuate fasciculus: consensus and controversy in the connectional anatomy of language. Brain 135:3529–3550

Dienes Z (2011) Bayesian versus orthodox statistics: which side are you on? Perspect Psychol Sci. https://doi.org/10.1177/1745691611406920

Farquharson S, Tournier JD, Calamante F, Fabinyi G, Schneider-Kolsky M, Jackson GD, Connelly A (2013) White matter fiber tractography: why we need to move beyond DTI. J Neurosurg 118:1367–1377

Geary DC, Hoard MK, Byrd-Craven J, Desoto MC (2004) Strategy choices in simple and complex addition: contributions of working memory and counting knowledge for children with mathematical disability. J Exp Child Psychol 88:121–151

Grabner RH, Ansari D, Reishofer G, Stern E, Ebner F, Neuper C (2007) Individual differences in mathematical competence predict

parietal brain activation during mental calculation. Neuroimage 38:346–356
Grotheer M, Jeska B, Grill-Spector K (2018) A preference for mathematical processing outweighs the selectivity for Arabic numbers in the inferior temporal gyrus. Neuroimage 175:188–200
Han BS, Hong JH, Hong C, Yeo SS, Lee DH, Cho HK, Jang SH (2010) Location of corticospinal tract at the corona radiata in human brain. Brain Res 1326:75–80
JASP Team (2017) JASP (Version 0.8.5) [Computer software]
Jeffreys H (1961) Theory of probability, 3rd edn. Oxford University, Oxford
Johansen-Berg H (2010) Behavioural relevance of variation in white matter microstructure. Curr Opin Neurol 23:351–358
Jones DK, Leemans A (2011) Diffusion tensor imaging. In: Modo M, Bulte JWM (eds) Magnetic resonance neuroimaging: methods and protocols. Humana, New York, pp 127–144
Kucian K, von Aster M, Loenneker T, Dietrich T, Martin E (2008) Development of neural networks for exact and approximate calculation: a fMRI study. Dev Neuropsychol 33:447–473
Kucian K, Ashkenazi SS, Hänggi J, Rotzer S, Jäncke L, Martin E, von Aster M (2014) Developmental dyscalculia: a dysconnection syndrome? Brain Struct Funct 219:1721–1733
Leemans A, Jeurissen B, Sijbers J, Jones DK (2009) ExploreDTI: A graphical toolbox for processing, analyzing, and visualizing diffusion MR data. In: Proceedings of the 17th Scientific Meeting, International Society for Magnetic Resonance in Medicine. Honolulu, p 3537
Li Y, Hu Y, Wang Y, Weng J, Chen F (2013) Individual structural differences in left inferior parietal area are associated with schoolchildren's arithmetic scores. Front Hum Neurosci 7:1–8
Martino J, Brogna C, Robles SG, Vergani F, Duffau H (2010) Anatomic dissection of the inferior fronto-occipital fasciculus revisited in the lights of brain stimulation data. Cortex 46:691–699
Matejko A, Ansari D (2015) Drawing connections between white matter and numerical and mathematical cognition: a literature review. Neurosci Biobehav Rev 48:35–52
Menon V (2015) Arithmetic in the child and adult brain. In: Cohen Kadosh R, Dowker A (eds) The Oxford handbook of numerical cognition. Oxford University, Oxford, pp 502–530
Moeller K, Willmes K, Klein E (2015) A review on functional and structural brain connectivity in numerical cognition. Front Hum Neurosci. https://doi.org/10.3389/fnhum.2015.00227
Navas-Sánchez FJ, Alemán-Gómez Y, Sánchez-Gonzalez J, Guzmán-De-Villoria JA, Franco C, Robles O, Desco M (2014) White matter microstructure correlates of mathematical giftedness and intelligence quotient. Hum Brain Mapp 35:2619–2631
Peters L, De Smedt B (2018) Arithmetic in the developing brain: a review of brain imaging studies. Dev Cogn Neurosci 30:265–279
Polspoel B, Peters L, Vandermosten M, De Smedt B (2017) Strategy over operation: neural activation in subtraction and multiplication during fact retrieval and procedural strategy use in children. Hum Brain Mapp 38:4657–4670
Prado J, Mutreja R, Zhang H, Metha R, Desroches AS, Minas JE, Booth JR (2011) Distinct representations of subtraction and multiplication in the neural systems for numerosity and language. Hum Brain Mapp 32:1932–1947
Rivera SM, Reiss AL, Eckert MA, Menon V (2005) Developmental changes in mental arithmetic: evidence for increased functional specialization in the left inferior parietal cortex. Cereb Cortex 15:1779–1790
Rykhlevskaia E, Uddin LLQ, Kondos L, Menon V (2009) Neuroanatomical correlates of developmental dyscalculia: combined evidence from morphometry and tractography. Front Hum Neurosci. https://doi.org/10.3389/neuro.09.051.2009
Schmahmann JD, Pandya DN (2008) Disconnection syndromes of basal ganglia, thalamus, cerebrocerebellar systems. Cortex 44:1037–1066
Shum J, Hermes D, Foster BL, Dastjerdi M, Rangarajan V, Winawer J, Parvizi J (2013) A brain area for visual numerals. J Neurosci 33:6709–6715
Thiebaut de Schotten M, Dell'Acqua F, Forkel SJ, Simmons A, Vergani F, Murphy DGM, Catani M (2011) A lateralized brain network for visuospatial attention. Nat Neurosci 14:1245–1246
Torbeyns J, Verschaffel L, Ghesquière P (2004) Strategic aspects of simple addition and subtraction: the influence of mathematical ability. Learn Instr 14:177–195
Tournier JD, Calamante F, Gadian DG, Connelly A (2004) Direct estimation of the fiber orientation density function from diffusion-weighted MRI data using spherical deconvolution. Neuroimage 23:1176–1185
Tournier JD, Calamante F, Connelly A (2007) Robust determination of the fibre orientation distribution in diffusion MRI: non-negativity constrained super-resolved spherical deconvolution. Neuroimage 35:1459–1472
Tsang JM, Dougherty RF, Deutsch GK, Wandell BA, Ben-Shachar M (2009) Frontoparietal white matter diffusion properties predict mental arithmetic skills in children. Proc Natl Acad Sci USA 106:22546–22551
Tuch DS (2004) Q-ball imaging. Magn Res Med 52:1358–1372
Van Eimeren L, Niogi SN, McCandliss BD, Holloway ID, Ansari D (2008) White matter microstructures underlying mathematical abilities in children. Neuroreport 19:1117–1121
Van Beek L, Ghesquière P, Lagae L, De Smedt B (2014) Left frontoparietal white matter correlates with individual differences in children's ability to solve additions and multiplications: a tractography study. Neuroimage 90:117–127
Van den Bos KP, Spelberg HCL, Scheepstra ASM, De Vries JR (1994) De Klepel: pseudowoordentest. Berkhout, Nijmegen
Vanderauwera J, Vandermosten M, Dell'Acqua F, Wouters J, Ghesquière P (2015) Disentangling the relation between left temporoparietal white matter and reading: a spherical deconvolution tractography study. Hum Brain Mapp 36:3273–3287
Von Der Heide RJ, Skipper LM, Klobusicky E, Olson IR (2013) Dissecting the uncinate fasciculus: disorders, controversies and a hypothesis. Brain 136:1692–1707
Wakana S, Caprihan A, Panzenboeck MM, Fallon JH, Perry M, Gollub RL, Mori S (2007) Reproducibility of quantitative tractography methods applied to cerebral white matter. Neuroimage 36:630–644
Wang R, Benner T, Sorensen AG, Wedeen VJ (2007) Diffusion toolkit: a software package for diffusion imaging data processing and tractography. In: 15th Annual Meeting, International Society for Magnetic Resonance in Medicine. Berlin
Wechsler D (2005) Wechsler Intelligence Scale for children—WISC-III-NL. Pearson, Amsterdam
Wedeen VJ, Hagmann P, Tseng WYI, Reese TG, Weisskoff RM (2005) Mapping complex tissue architecture with diffusion spectrum magnetic resonance imaging. Magn Reson Med 54:1377–1386
Woodcock RW, McGrew KS, Mather N (2003) Woodcock–Johnson III tests of achievement. Riverside, Itasca
Zhao J, Thiebaut de Schotten M, Altarelli I, Dubois J, Ramus F (2016) Altered hemispheric lateralization of white matter pathways in developmental dyslexia: evidence from spherical deconvolution tractography. Cortex 76:51–62