The Artists' Brain: A Data Fusion Approach to Characterize the Neural Bases of Professional Visual Artists

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Conflict of interest statement

The authors declare no conflict of interest.

Abstract

Artistic creativity relies on complex perceptual, cognitive and motoric functions, yet the specific neural characterization of being an artist remain incompletely understood. To fill this gap in the literature, the present study aims to characterize the gray matter (GM) and white matter (WM) contributions to professional visual artists as compared to non-artists controls. The MRI brain scans of 12 professional artists and 12 matched non-artists were analyzed via an unsupervised machine learning method known as Transposed Independent Vector Analysis (tIVA) to detect joint GM-WM networks. Two independent networks were found. The first network (IC2), more expressed in artists, included increased GM-WM concentration in regions associated with the Default Mode Network (DMN), Executive Control Network (ECN), and sensorimotor networks possibly related with augmented cognitive and ideational control, and increased perceptual-motor integration skills critical for creative tasks. The second network (IC8), less expressed in artists, included decreased GM-WM density in regions related to the Salience Network, such as the Anterior Cingulate Cortex, suggesting attentional regulation processes that may not be as central to visual artists. In sum, these results suggest that artists may rely on specialized brain networks, reflecting unique neural adaptations in individuals with pronounced creativity and extensive creative training.

Key Words: art, artist, creativity, neuroscience, data fusion, machine learning

Introduction

Artistic creativity is a fundamental aspect of human cognition, that enriches the world with art products stemming from music, paintings, design and many more, that drove cultural evolution across history (Heilman et al., 2003; Acosta, 2014). Traditionally, scholars like Guilford (1950) viewed creativity as the ability to generate novel and meaningful ideas through flexible thinking and effective problem-solving. Building on Guilford's early work on divergent thinking—the process of generating multiple solutions to a problem (Guilford et al., 1967) — recent perspectives have shifted to align with cognitive science. De Pisapia & Rastelli (2022), for example, suggest that creativity is a structured cognitive process, positioning it as a systematic information-processing function rather than a mystical or purely innate trait.

The origins of artistic creativity can be traced back to early human societies, where symbolic artifacts—such as beads, ochres, and body decorations—reflect the beginnings of abstract thought and social complexity. Archaeological findings from sites like Blombos Cave in South Africa suggest that these early artistic expressions served a purpose beyond mere decoration; they likely played an essential role in social bonding and cultural transmission (McBrearty & Brooks, 2000; Henshilwood et al., 2009). According to Morriss-Kay (2010) and Zaidel et al. (2013), such symbols may have functioned similarly to language, helping to establish shared meanings that reinforced group identity and facilitated complex social interactions. Some researchers, including Miller (2001) and Møller & Petrie (2002), even propose that the aesthetic and symbolic dimensions of art were shaped by evolutionary pressures like sexual selection, where creative displays could confer social status or reproductive advantages. Together, these perspectives underscore that artistic creativity is not

merely an ornamental trait but a foundational aspect of human development, deeply intertwined with our cognitive and social evolution and encoded in specific brain networks.

In contemporary neuroscience, creativity is increasingly seen as the product of interactions across distributed brain networks. Instead of being attributed solely to innate talent or divine inspiration, creativity is now recognized as a complex cognitive process rooted in brain architecture (Jung et al., 2013; Sporns, 2014). Central to this understanding are two major brain networks: the default mode network (DMN) and the executive control network (ECN) (Buckner et al., 2008; de Souza et al., 2014). The DMN, which includes regions such as the medial prefrontal cortex, posterior cingulate cortex, and medial temporal lobes, supports self-referential thought, mind-wandering, and mental simulations—cognitive processes that enable the generation of novel ideas (Buckner & Di Nicola, 2019; Andrews-Hanna et al., 2010). During creative tasks, the DMN is particularly active, allowing for ideational flexibility and the spontaneous formation of unique connections, which are essential for divergent thinking (Christoff et al., 2009; Beaty et al., 2014). In contrast, the ECN encompasses regions like the dorsolateral prefrontal cortex and anterior cingulate cortex, which are involved in cognitive control, evaluative processing, and planning (Kowatari et al., 2009; Levy & Volle, 2009). While the DMN generates raw, unstructured ideas, the ECN critically assesses and organizes these ideas into coherent and meaningful outputs (Bressler & Menon, 2010). This interplay between ideation and critical refinement is essential for artistic creativity, as the ECN modulates spontaneous ideas from the DMN, balancing open-ended imagination with goal-directed thought—a dynamic particularly important for creating structured artistic expressions (Beaty et al., 2014; Takeuchi et al., 2011).

Recent neuroimaging studies in non-artists or individuals undergoing a creative training, provide empirical support for this dual-network model. Techniques like functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) show that tasks requiring

creativity often activate both the DMN and ECN simultaneously, allowing for the integration of spontaneous ideation with evaluative processing (Beaty et al., 2014; Jung et al., 2013). For example, fMRI studies have demonstrated that creative tasks such as narrative comprehension and insight problem-solving involve coordinated activation of these networks, reducing competition between them and fostering a unique mental state where ideas can be generated, critically analyzed, and refined (Christoff et al., 2009; De Pisapia et al., 2016; Spreng & Grady, 2010; Mason et al., 2007). Individual differences in creative abilities appear to be linked to the strength of connectivity within and between the DMN and ECN. Beaty et al. (2018) used connectome-based predictive modeling to show that individuals with stronger DMN-ECN connectivity tend to perform better on divergent thinking tasks, suggesting that enhanced connectivity facilitates greater originality and fluency in creative ideation. This connectivity is especially prominent in professional artists, who often display significant neuroplastic changes associated with their expertise (Pascual-Leone et al., 2005).

In addition to functional differences, recent studies using diffusion tensor imaging (DTI) have explored how white matter integrity relates to creativity in non-artists and individuals undergoing creative training. Findings suggest a complex, sometimes contradictory relationship. For instance, Takeuchi et al. (2010a) found that higher fractional anisotropy (FA) values in frontal white matter pathways and the corpus callosum were positively correlated with creativity scores, suggesting that enhanced WM integrity may facilitate efficient inter-regional communication necessary for creative thought. In contrast, Jung et al. (2010) observed that lower WM integrity in specific areas might enhance creativity by reducing inhibitory control, enabling more flexible and divergent thinking—an effect similarly reported by Wertz (2020). While these studies provide valuable insights into the role of white matter in creativity, they have focused exclusively on general, non-specialized populations and relied on behavioral test scores as measures of creativity. This leaves

unanswered questions about how white matter integrity might differ in professional visual artists, whose creativity stems from years of training and expertise.

Further insights into this gap might come from examining how neurological conditions affect creative behaviors both in non-artists and in real artists. Research on patients with frontotemporal lobar degeneration (FTLD), Alzheimer's disease (AD), and Parkinson's disease (PD) reveals how disruptions in neural pathways impact creativity differently (Acosta, 2014; Miller et al., 2004). For instance, FTLD patients often exhibit unexpected artistic behaviors in non-artists, creating detailed artwork despite cognitive decline, likely due to preserved visuospatial skills in the right parietal cortex (Rankin et al., 2007; Acosta, 2014). In contrast, AD patients typically show a decline in creative output, producing simpler and less colorful works as degeneration affects regions involved in memory and abstraction (Crutch et al., 2001). Similarly, PD patients receiving dopaminergic therapy have shown increased creative activity, particularly in tasks involving divergent thinking and metaphorical creativity. This heightened creativity is linked to elevated dopamine levels, which enhance novelty-seeking and ideational fluency. Interestingly, this effect appears independent of impulse control disorders, suggesting that dopaminergic therapy may selectively boost certain domains of creativity (Faust-Socher et al., 2014; Acosta, 2014). While these findings provide valuable insights into how specific brain regions influence creativity, they primarily focus on clinical or non-specialized populations. As a result, little is known about how years of professional training and expertise in visual arts shape the brain's neural pathways and their relationship to creative processes.

An alternative line of research has focused on professional visual artists who have suffered neurological conditions. Numerous case studies have provided causal evidence of how specific impairments influence creativity and artistic style (Pelowski et al., 2022). For

example, German painter Lovis Corinth suffered a right-hemispheric stroke that caused visuo-spatial hemineglect and motor deficits, leading to planar compositions, reduced spatial depth, and vivid colors, reflecting a shift from Impressionism to Expressionism (Blanke & Pasqualini, 2012). Similarly, William Utermohlen, diagnosed with probable Alzheimer's disease, transitioned from realistic self-portraits to fragmented, abstract works with blurred features and coarse brushstrokes, mirroring his cognitive decline (Crutch, Isaacs, & Rossor, 2001). French painter Paul-Elie Gernez, after a stroke resulting in Wernicke's aphasia, shifted from poetic, dreamlike works to more concrete and realistic depictions, showing reduced spontaneity but preserved technical quality (Boller et al., 2005). While these studies reveal important links between neurological conditions and artistic creativity, they primarily focus on the effects of impairments, leaving unanswered questions about how creativity functions in the healthy, highly trained brains of professional artists.

Considering these gaps, recent studies have begun to investigate the neural basis of creativity in professional visual artists with healthy, undamaged brains. To date, only two such studies have been conducted (De Pisapia et al., 2016; Grecucci et al., 2023). In a study by De Pisapia et al. (2016), the connectivity patterns in professional visual artists and non-artists were assessed during creative tasks. This study found that artists showed significantly stronger connectivity between the DMN and ECN during the creative task (planning a work of visual art on an assigned topic). This enhanced connectivity enables artists to balance abstract ideation with goal-directed execution, facilitating a more seamless integration of imagination and evaluative control, which is crucial for the demands of complex artistic tasks (Beaty et al., 2014; Mason et al., 2007).

From a structural point of view, some evidence suggest that the brain of professional artists may be different in terms of both gray matter (GM). One study by Grecucci et al.

(2023) employed multi-kernel learning (MKL), a supervised machine learning technique, to analyze brain structure in professional artists. This study found that artists had increased GM density in regions such as Heschl's gyrus, the amygdala, and the temporal pole—areas linked to sensory processing, emotional regulation, and mental imagery. These structural characteristics may underlie artists heightened emotional depth and visualization abilities, potentially reflecting neural adaptations that support key functions for creative expression (Chamberlain et al., 2014; Shi et al., 2017).

Despite significant advancements in neuroscience, our understanding of the neural characterization of being an artist remains incomplete, particularly when it comes to the combined roles of gray matter (GM) and white matter (WM). Traditionally, studies have examined GM and WM separately, an approach that overlooks the intricate interplay between these components. White matter pathways facilitate communication between different brain regions, and their integrity is essential for efficient neural processing and cognitive functioning (Fields, 2008). Some studies have found positive correlations between WM integrity and creativity measures (Takeuchi et al., 2010a; Jung et al., 2010), while others report negative correlations (Wertz et al., 2020). These inconsistencies highlight a gap in the literature and underscore the need for methodologies that can simultaneously assess the combined impact of GM and WM on artistic cognition rather than general creativity.

To address the limitations of mass univariate analysis, researchers have increasingly turned to advanced multivariate techniques, particularly unsupervised machine learning methods that can uncover hidden patterns in complex datasets without predefined assumptions (Vieira, Pinaya, & Mechelli, 2020). One such approach is transposed Independent Vector Analysis (tIVA), an extension of Independent Component Analysis (ICA) that allows for the integration of GM and WM data into joint profiles, decomposing the brain into covarying networks (Adali, Levin-Schwartz, & Calhoun, 2015). Unlike traditional univariate analyses

that focus on isolated brain regions, tIVA captures natural co-activating networks across the entire brain, offering a holistic view of brain structure and function (Grecucci et al., 2022; Hebart & Baker, 2018). This approach is particularly well-suited for studying artistic creativity, which is thought to emerge from distributed networks rather than isolated regions (Sporns, 2014).

Fusion methods like tIVA have shown promising results in identifying distributed neural networks linked to complex psychological traits and disorders. For example, they have been applied to the study of emotional intelligence and anxiety (Grecucci et al., 2024a), trait anxiety (Baggio et al., 2023a; Baggio et al., 2023b), phobic disorders (Scarano et al., 2024), and personality characteristics such as psychopathy and the Dark Triad (Bakiaj et al., under review; Jornkokgoud et al., 2024). These studies demonstrate that fusion approaches can reveal patterns in neural data that may be overlooked by traditional methods, offering insights into the distributed brain networks associated with psychological phenomena.

Compared to standard techniques such as diffusion tensor imaging (DTI), which is commonly used to assess WM integrity, fusion methods provide significant advantages. While DTI measures the microstructural displacement of water molecules within WM fibers to infer integrity (Assaf & Pasternak, 2008; Alba-Ferrara & de Erausquin, 2013), it is highly sensitive to noise and may yield poor reproducibility across regions of interest (Radwan et al., 2022; Baggio et al., 2023a). In contrast, fusion methods allow researchers to analyze WM characteristics in a distributed manner, without being constrained to specific tracts. By combining GM and WM data via structural MRI, fusion methods reduce computational demands by focusing on meaningful information, minimizing the risk of overfitting and enhancing the robustness of findings (Guyon & Elisseeff, 2003).

Current Study Design and Hypotheses

Building upon this methodological foundation, our study aims to investigate the structural differences between professional visual artists vs non artists, by applying tIVA to find joint information in the GM and WM modalities. Twelve professional visual artists and twelve matched non-artists were used to this aim. We hypothesize that professional artists will exhibit increased GM-WM density, in networks overlapping with the Default Mode Network (DMN) and the Executive Control Network (ECN). The DMN is associated with spontaneous ideation and imaginative thought (Beaty et al., 2014; Jung et al., 2013), while the ECN supports executive functions and evaluative processes necessary for refining creative ideas (Ellamil et al., 2012; Saggar et al., 2015). Given artists' intensive visual and spatial training, we also anticipate finding structural variations in regions associated with visual processing and imagery, including the occipital lobe, thalamus, and areas within the parietal and temporal lobes. Such findings would further underscore the roles of these networks in artistic creativity, highlighting the integration of ideation, evaluation, and sensory processing.

Moreover, considering the physical demands of tasks like painting and sculpting, we hypothesize that artists will show differences in sensory-motor areas, such as the motor cortex and somatosensory cortex, which are involved in fine motor control (Ferri et al., 2012). The continuous engagement of these regions in detailed artistic tasks suggests that professional artists may develop more efficient sensory-motor networks, enabling them to translate complex visual imagery into precise physical actions. This refined sensory-motor integration may enhance their capacity for bodily awareness and nuanced control, both essential for creating expressive and technically skilled artworks. We also expect to find reduced gray matter-white matter density in areas linked to the Salience Network (SN). This is because visual artists might prioritize cognitive and emotional processes that differ from the usual salience-driven focus on immediate social or homeostatic demands. Instead, their brains may

adapt to emphasize networks that support creativity and introspection—such as the Default Mode Network (DMN) or the Executive Control Network (ECN). As a result, this shift in priorities could lead to a corresponding decrease in the integrity of the SN.

Materials and Methods

Participants

The study involved a total of 24 participants (14 males and 10 females), consisting of 12 professional artists and 12 non-artists matched for age and education. All participants were right-handed and reported no history of psychiatric or neurological disorders, nor any use of drugs affecting the central nervous system. The professional artists were recruited with the assistance of the Museum of Modern and Contemporary Art (MART) in Rovereto, Italy. Among the artists, nine have formal training from art schools or academies, where they studied foundational visual elements—such as color, form, line, space, texture, and value—and developed expertise in techniques like sketching, drawing, and painting from life. This training involved mastering proportions, shading, and three-dimensional modeling. The remaining three artists are self-taught, having honed their skills independently, though they lack the structured curriculum of formal art education. The control group comprised individuals whose professions and skills were unrelated to drawing or any visual arts. They were recruited through local advertisements. To ensure that control participants were not involved in visual artistic activities, they were asked prior to the study if they were professional artists or engaged in visual arts, and all confirmed they were not. Additionally, in a previous functional study involving the same participants, everyone was required to create a drawing after the MRI session (De Pisapia et al., 2016). This exercise allowed us to verify that none of the control participants possessed professional-level drawing abilities. The two

groups were closely matched for age and gender. The mean age of the artists was 30.9 years, while that of the non-artists was 29.76 years ($p = 0.58$). Gender distribution was comparable between the groups, with the artist group consisting of 4 females and 8 males, and the control group comprising 6 females and 6 males ($p = 0.43$). All procedures were conducted in accordance with relevant guidelines and regulations and received approval from the University of Trento Ethics Committee. Informed consent was obtained from all participants prior to their inclusion in the study. Participants received reimbursement for travel expenses incurred while reaching the neuroimaging laboratory. Moreover, they consented to have their anonymized experimental findings and resulting sketches and artworks included in a museum exhibition titled “In Resonance: Snapshots of Creativity in the Brain” at MART, Rovereto, Italy (Bacci, 2013). Their work was also featured in the exhibition's illustrated catalogue, providing an additional incentive for participation.

Behavioral Assessment: Vividness of Visual Imagery Questionnaire (VVIQ)

All participants underwent a behavioral assessment using the Vividness of Visual Imagery Questionnaire (VVIQ), a self-report measure designed to evaluate an individual's capacity for visual imagery. The VVIQ consists of 16 items, each prompting participants to visualize a specific scenario or object. For each item, participants rate the vividness of their mental image on a scale from 1 to 5. A rating of 1 signifies an image that is "perfectly clear and as vivid as normal vision," while a rating of 5 indicates "no image at all—you only know that you are thinking of the object" (Marks, 1973). Therefore, lower scores reflect higher vividness of mental imagery, whereas higher scores denote lower vividness. This assessment allowed us to quantify and compare the visual imagery abilities of professional artists and non-artists.

Imaging Data Acquisition

All participants were screened for MRI compatibility by a medical professional. Eligible individuals proceeded to the MRI scanning session, which initially included both anatomical and functional imaging. Anatomical data were collected during the first 6 minutes of the session, followed by functional imaging as described in previous study (De Pisapia, 2016). However, for the purposes of our study, only structural (T1-weighted) images were utilized. Brain imaging was conducted using a 4 Tesla Bruker MedSpec Biospin MR scanner equipped with a birdcage transmit and an 8-channel radio-frequency head receiver coil. To minimize head movement, participants' heads were stabilized with foam padding. T1-weighted anatomical scans were acquired using the MP-RAGE sequence with the following parameters: voxel resolution of $1 \times 1 \times 1$ mm³, field of view (FOV) of 256×224 mm², 176 slices, GRAPPA acquisition with an acceleration factor of 2, repetition time (TR) of 2700 ms, echo time (TE) of 4.18 ms, inversion time (TI) of 1020 ms, and a flip angle of 7 degrees.

Preprocessing

All T1-weighted structural images underwent a quality assessment to exclude any artifacts prior to analysis. Preprocessing was performed using SPM12 (Statistical Parametric Mapping; https://www.fil.ion.ucl.ac.uk/) (Penny et al., 2011) in conjunction with the Computational Anatomy Toolbox (CAT12; http://www.neuro.uni-jena.de/cat/) (Gaser et al., 2024) within the MATLAB environment. Initially, each image was re-oriented to position the anterior commissure at the origin. Following re-orientation, the images were segmented into gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF) using CAT12. Subsequent registration was conducted using Diffeomorphic Anatomical Registration through Exponential Lie algebra tools (Ashburner, 2007), which facilitates a whole-brain approach to align anatomical structures across participants. After registration, the DARTEL-normalized

images were transformed to the Montreal Neurological Institute (MNI) space. To prepare the data for further analysis, a spatial Gaussian smoothing with a kernel size of 10 mm, [10 10 10] was applied, enhancing the signal-to-noise ratio and accommodating individual anatomical variability**.**

Unsupervised Machine Learning Procedure

To comprehensively analyze the neural correlates of the artist brain, we employed Transposed Independent Vector Analysis (tIVA), an advanced unsupervised machine learning method, to fuse gray matter (GM) and white matter (WM) data. The decision to include both GM and WM components in our analyses is motivated by their informative value and shared genetic influences, which provide a more holistic understanding of brain structure and function (Baggio et al., 2023a; Spalletta, Piras, & Gili, 2018). Traditional Independent Component Analysis (ICA) methods, such as joint ICA (jICA), assume shared mixing profiles across different modalities, limiting their effectiveness when modality correlations vary. In contrast, tIVA extends ICA by allowing each modality to maintain separate profiles while preserving higher-order statistical structures, thereby accommodating varying degrees of correlation between GM and WM data (Adali et al., 2015). For the fusion of GM and WM data, we used segmented, high-resolution structural MRI (sMRI) data for both the artist and control groups. GM represents regions dense with neuron cell bodies essential for processing information, while WM consists of myelinated axons facilitating communication between these GM areas. Integrating GM and WM through tIVA allows for the identification of patterns that contribute to cognitive functions and structural differences, offering insights often missed in single-modality analyses (Adali et al., 2015). The analysis was performed in the MATLAB R2023a environment using the Fusion ICA Toolbox (Calhoun, Adali, Pearlson, & Kiehl, 2006). We predefined the number of components to 10 to ensure that the extracted

components could adequately capture the structural complexity and variability within our dataset, as the data-driven estimation yielded only three components due to the low number of participants, which were considered insufficient for this purpose. To ensure the reliability of each modality, we employed the ICASSO (Himberg, Hyvärinen, & Esposito, 2004; Himberg & Hyvärinen, 2003) and FastICA algorithms, enhancing the stability and reproducibility of the extracted components.

The tIVA output was a matrix with loading coefficients across participants, where rows represented individual subjects and columns denoted loading coefficients for each independent component. These coefficients indicate the degree to which each component is expressed in every participant, particularly in terms of GM and WM concentrations compared to an average across the brain (See in Figure 1). Subsequently, the independent components were mapped into Talairach coordinates using groupICA software (https://trendscenter.org/software/), enabling the anatomical localization of identified components. Finally, we visualized the independent components using Surf Ice (https://www.nitrc.org/projects/surfice/), highlighting brain regions with higher (positive values) GM and WM concentrations using separate templates for GM and WM. To determine which components were significantly more and less represented in artists compared to controls, we conducted two independent one-tailed t-tests on each of the 10 components using JASP software (JASP Team, 2024; JASP Version 0.19.0), using the two contrasts (artist>controls, artists<controls).

Figure 1.

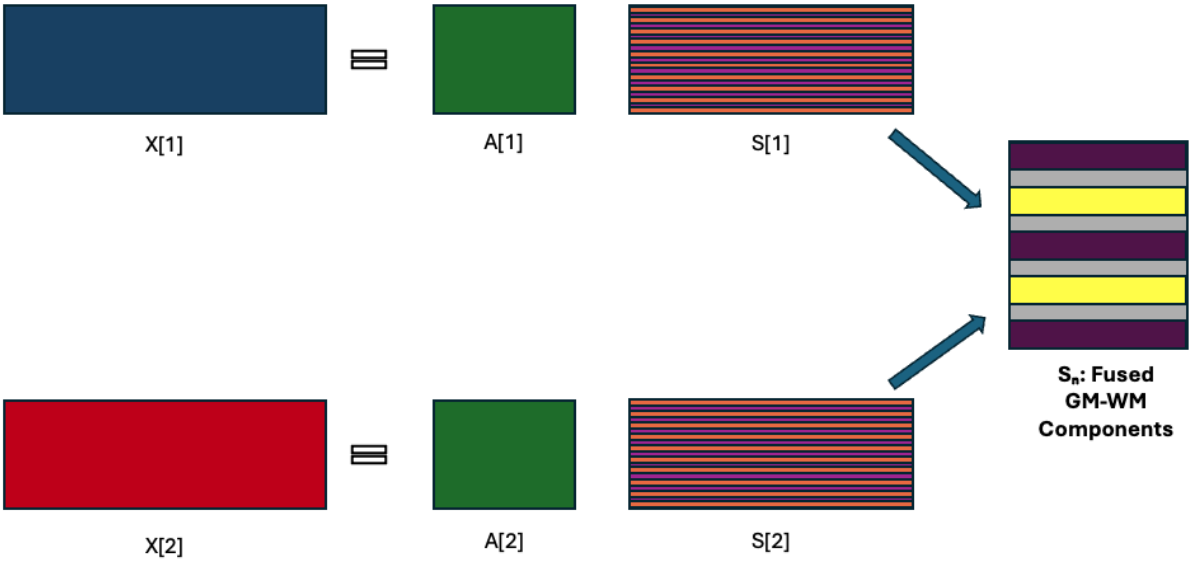

Figure 1 illustrates the application of Transposed Independent Vector Analysis (tIVA) to combine gray matter (GM) and white matter (WM) data, enabling the identification of neural patterns that differentiate artists from controls. In this process, X[1] and X[2] represent the original data matrices for GM and WM, respectively, with each matrix containing data for all subjects (both artists and controls). These input matrices are decomposed into mixing matrices (A[1] and A[2]) and source component matrices (S[1] and S[2]). The mixing matrices, A[1] for GM and A[2] for WM, provide subject-specific loadings for each component, indicating the degree to which each component is expressed in each individual. The source component matrices, S[1] and S[2], capture the independent patterns within each modality, highlighting specific brain structures in GM and WM. These modality-specific components are then fused into a combined matrix, S_n: Fused GM-WM Components, which captures joint patterns across GM and WM, allowing us to examine shared and distinct neural structures that differentiate artists from controls.

Results

Unsupervised Machine Learning Results

tIVA estimated 10 joint GM-WM networks. Each network represented a set of brain regions covarying in the two modalities. Before proceeding with statistical analyses, all components were visually inspected to exclude potential artifacts. No components were excluded, and all independent components (ICs) were included in the subsequent analyses. The contrast Artist > Control, returned one component to be significant: IC2 ($t = 2.012$, $df = 22$, $p = 0.028$, Cohen's $d = 0.821$). IC2 includes regions such as Thalamus, Precuneus, Cuneus, Fusiform Gyrus, Inferior Parietal Lobule, Pre and Post Central Gyrus, Helsch Gyrus, Parahippocampal Gyrus, Cerebellum, Caudate Nucleus, Posterior Cingulate Cortex (PCC) that exhibit increased GM-WM density (See Figure 2 below and Tables 1 and 2 in the Annex) in artist compared to controls. No other components were significant ($p<0.05$). The contrast Artist < Control returned one component, IC8 ($t = -2.816$, $df = 22$, $p = 0.005$, Cohen's $d = -1.150$), including regions such as Anterior Cingulate Cortex (ACC), Middle Frontal Gyrus (MFG) that exhibit decreased GM-WM density in artists compared to controls. No other components were significant ($p<0.05$). See Figure 3 below and Tables 3 and 4 in the Annex.

Figure 2.

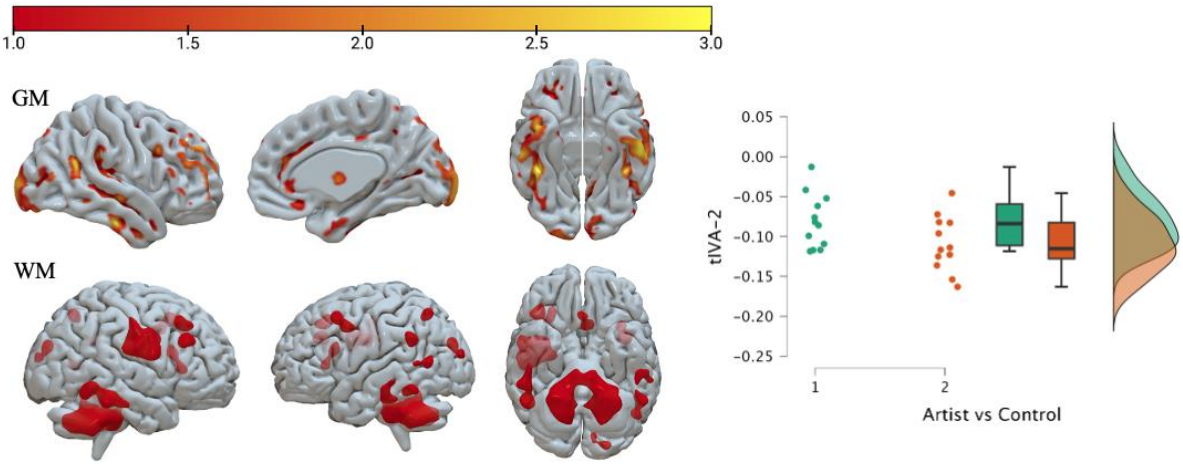

Figure 2.: tIVA-2 Brain plots. From left to right are displayed brain plots of tIVA-GM2 of the right hemisphere in medial view, of the right hemisphere in lateral view, and of both hemispheres in inferior view (top), and brain plots of tIVA-WM2 of the right hemisphere in medial view, of the left hemisphere in medial view, and of both hemispheres in inferior view (bottom). Regions with increased GM are represented with warmer colors. The right panel presents boxplots and data distributions for IC2 (tIVA-2) that is significantly more expressed in artists (t = 2.012, p = 0.028).

Figure 3.

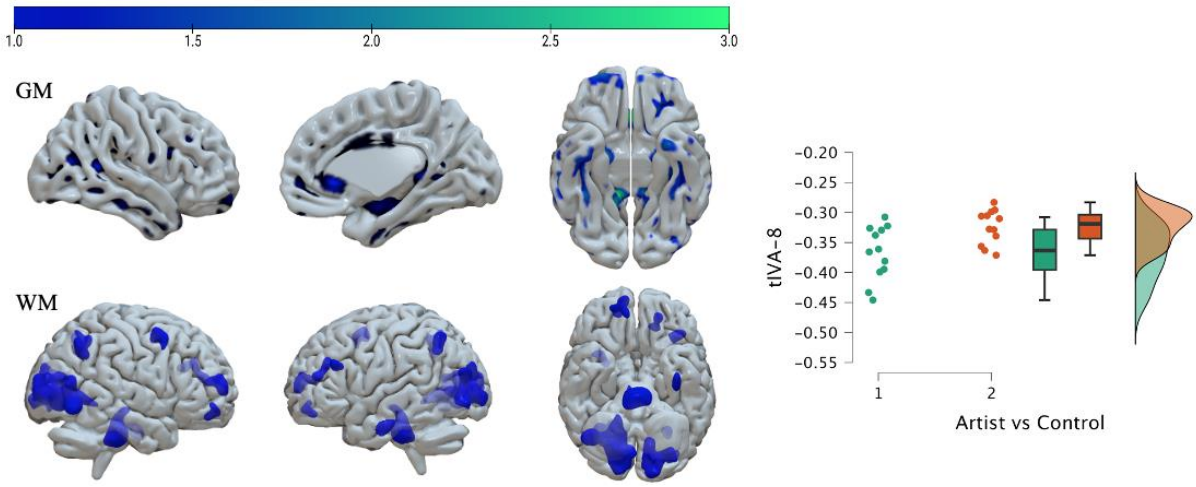

Figure 3.: tIVA-8 Brain plots. From left to right are displayed brain plots of tIVA-GM8 of the right hemisphere in medial view, of the right hemisphere in lateral view, and of both hemispheres in inferior view (top), and brain plots of tIVA-WM8 of the right hemisphere in medial view, of the left hemisphere in medial view, and of both hemispheres in inferior view (bottom). Regions with increased GM are represented with warmer colors. The right panel presents boxplots and data distributions for IC8 (tIVA-8) that is significantly less expressed in artists (t = -2.816, p = 0.005).

Relationships Between Neural Components, Visual Imagery Vividness, and Inter-Component Correlation

The Spearman correlation between IC2 and VVIQ scores did not yield any significant result (Spearman's rho = 0.048, p = 0.582). In contrast, the correlation analysis for IC8 revealed a significant positive association with VVIQ scores (Spearman's rho = 0.384, p = 0.043). This positive correlation indicates that higher loading coefficients for IC8 are associated with higher VVIQ scores, meaning that participants with greater expression of IC8 tend to have lower visual imagery vividness. Since IC8 was less expressed in the Artists group, this result aligns with our expectation that Artists, who generally report higher imagery vividness, would exhibit lower IC8 expression.

Additionally, we investigated the relationship between IC2 and IC8 to explore whether these components exhibit a complementary or inverse structural pattern between groups. Pearson's correlation analysis revealed a significant negative correlation between IC2 and IC8 (r = -0.472, p = 0.020), suggesting that as the expression of IC2 increases, the expression of IC8 tends to decrease. This inverse relationship further supports the distinction between these components.

Discussion

The aim of this study was to test the hypothesis that the artist's brain is different compared to non-artists in terms of specific GM-WM networks. To test this hypothesis, we analyzed 12 professional visual artists recognized by the international art system and 12 matched controls without any experience in art. Using transposed Independent Vector Analysis (tIVA; Adali, Levin-Schwartz, & Calhoun, 2015), an unsupervised machine learning technique, we aimed to analyze the combined contributions of gray matter (GM) and white matter (WM) structures in these individuals, allowing us to identify neural networks

supporting the specific cognitive and perceptual demands of artistic creation. This approach represents the first application of tIVA specifically focused on GM-WM fusion to investigate the artist brain.

Our analysis identified two distinct components, IC2 and IC8, that exhibited significant group differences between artists and non-artists. IC2, which was more expressed in artists (increased GM-WM density) and included brain regions associated with the Default Mode Network (DMN), Executive Control Network (ECN), Visual System and Sensorimotor Networks. Specifically, IC2 encompassed regions such as the Thalamus, Fusiform Gyrus, Postcentral and Precentral Gyri, Cuneus, Precuneus, Inferior Parietal Lobule, Inferior Frontal Gyrus, and Superior Frontal Gyrus. Notably, although the thalamus is not typically considered part of the DMN, it has been reported to show strong functional connectivity with the DMN's precuneus during resting states (Tomasi & Volkow, 2011; Zhang & Li, 2012). Historically considered a passive relay station, recent research has highlighted the thalamus's active role in integrating and maintaining mental representations (Wolff & Vann, 2018), indicating its potential role in supporting internally guided cognitive processes relevant to artistic creation. The right Fusiform Gyrus, also represented in IC2, is specialized for processing facial information, including recognizing faces and interpreting facial expressions, which are essential for understanding social cues (Adolphs, 2001; Shultz et al., 2015). According to the cultural recycling hypothesis, the right FG becomes increasingly specialized for face recognition as the left FG adapts to word recognition with the development of reading skills (Dehaene & Cohen, 2007). This representation in the right FG may reflect enhanced perceptual processing abilities in artists, particularly in interpreting social and emotional cues. Moreover, a particularly notable finding in IC2 was the representation of Heschl's Gyrus, consistent with prior work by Grecucci et al. (2023), which identified this region as a key

neural marker distinguishing artist from non-artists in a supervised machine learning approach limited to GM features.

Additionally, the inclusion of the Inferior Temporal Gyrus (ITG) in IC2 is significant. The ITG is essential for high-level visual processing, including object recognition, visual memory, and semantic cognition (Lin et al., 2020). Its ability to create and manipulate meaningful visual representations suggests it might contribute to visual creativity by enabling the generation of novel and contextually relevant imagery. This aligns with artists' need to generate and interpret complex visual stimuli, supporting both perceptual and complex cognitive functions (Davey et al., 2016).

IC2's inclusion of DMN regions such as the Cuneus and Precuneus supports the idea that this component facilitates ideational flexibility and internally guided thought, key elements in creative cognition. Utevsky (2014) demonstrate the significance of the Cuneus and Precuneus in fostering originality and cognitive flexibility, which are essential for creativity. The ECN, with regions like the Inferior and Superior Frontal Gyrus, provides cognitive control, evaluative processing, and planning, essential for structuring and refining creative ideas (Kowatari et al., 2009; Levy & Volle, 2009). In the study by De Pisapia et al. (2016), higher DMN-ECN connectivity observed in artists during creative tasks provided evidence of enhanced functional connectivity compared to non-artists. Similarly, in our study, the representation of regions associated with both the DMN and ECN within IC2 may serve as evidence for underlying structural connectivity that supports creative processes. Together, these findings might suggest artists may exhibit both functional and structural connectivity patterns that facilitate creative cognition. Similarly, Takeuchi et al. (2010b) observed positive correlations between GM volume in the right dorsolateral prefrontal cortex and precuneus with creative potential, supporting the idea that these regions underpin cognitive flexibility and working memory in creative individuals. Our finding of increased GM volume in the

Precuneus within IC2 for artists aligns with these results, suggesting that this structural adaptation may support the cognitive demands of complex artistic tasks, which require both sustained attention and the flexibility to explore novel ideas.

Furthermore, previous studies, such as Chamberlain et al. (2014), identified positive relationships between artistic training and GM density in the cerebellum. This aligns with our observation of cerebellar regions within IC2, including the Culmen and Cerebellar Tonsil. The Culmen, located at the top of the cerebellar vermis, has been implicated in the refinement of thought and language. Vandervert and Vandervert-Moe (2020) argue that the cerebellum, in collaboration with the cerebral cortex, plays a leading role in creativity by decomposing behavior and thought so that they can be recombined to provide new and useful solutions to problems, and by automatically sending refinements of behavior and thought to the cerebral cortex, where they are experienced intuitively. The cerebellar vermis, including the Culmen, plays a key role in regulating affect, cognition, and behavior by acting as part of a neural circuit involving the limbic system and prefrontal cortex (Schmahmann, 2000). Its involvement in IC2 indicates that cerebellar regions may contribute not only to fine motor skills and perceptual-motor integration but also to higher-order cognitive processes essential in visual art practice.

IC8, which was less expressed in artists compared to non-artists, includes regions associated with the Salience Network (SN), including the Anterior Cingulate Cortex (ACC) and regions such as Medial Frontal Gyrus (MFG), Cingulate Cortex. The SN is known for its role in attentional regulation and monitoring of cognitive control processes (Uddin, 2016), which may support general attentional and regulatory functions. The representation of the ACC within IC8 might suggests that this component may facilitate attentional focus and regulatory processes, reflecting cognitive processes in non-artists that are oriented more

towards attentional demands than the perceptual and motor processes more represented in IC2. This finding aligns with Shi et al. (2016), who found that artistic creativity was negatively associated with GM volume in the ACC, a core region of the SN, suggesting that higher ACC involvement may be more characteristic of non-artistic cognitive processing. Furthermore, the MFG is less expressed in professional artists, which may be due to the demands of their artistic pursuits, which priorities visual-spatial processing, sensory integration and creative ideation over executive functions typically mediated by this region. Structurally, the medial frontal gyrus supports executive tasks such as planning, error monitoring and decision-making (Rushworth et al., 2004), which may be less critical in professions such as visual arts, where abstract and divergent thinking dominates. These results also partially overlap with the study by Wertz et al. (2020), in which they found that lower FA left middle frontal gyrus correlated with higher divergent thinking scores.

The positive correlation observed between IC8 and VVIQ scores also showing that higher IC8 representation is associated with lower vividness of visual imagery. This could imply that IC8's configuration, less prominent in professional visual artist, may not be as strongly associated with mental imagery, which aligns with previous findings that non-artists tend to score lower on imagery vividness (De Pisapia et al., 2016). This correlation might suggest that artists rely less on attentional tasks and more on those involving vivid mental imagery. However, further research is needed to confirm this relationship and to better understand the specific role of IC8 in visual imagery.

In contrast, no significant correlation was found between IC2 and VVIQ scores. This lack of correlation suggests that while IC2 is more represented in artists and may support creative processes, its contribution is not limited to visual imagery alone. IC2 may support broader creative cognition, potentially encompassing ideation, motor integration, and evaluative

processes. This finding points to a possible specialization in IC2 beyond vivid imagery, suggesting that creativity may involve a range of cognitive processes that extend beyond the mental visualization typically measured by VVIQ.

The inverse correlation between IC2 and IC8 suggests that these components may play complementary roles. The increased representation of IC2 in artists may reduce the need for the attentional regulation functions typically associated with IC8. Similarly, the reduced representation of IC8 in artists might reflect a diminished reliance on networks that prioritize generalized attentional functions. This inverse relationship between IC2 and IC8 highlights potential differences in network usage between the groups, though further research is needed to fully understand the implications of this finding.

Conclusion and limitations

By combining gray matter (GM) and white matter (WM) data, we identified neural networks that may support the specific cognitive and perceptual demands of artistic creativity. Our findings highlighted the involvement of the Default Mode Network (DMN), Executive Control Network (ECN), and sensorimotor networks, suggesting that these brain structures could underlie the ideational flexibility, cognitive control, and perceptuomotor integration essential in artistic practice. The inclusion of both GM and WM components enhances the comprehensiveness of our findings and sheds light on the structural adaptations associated with professional artists' brains.

However, it is important to acknowledge the limitations of this study. First, the sample size of 12 professional artists is quite small. However, the reader must consider the difficulty of finding real professional visual artists as recognized by the international art system. However, we acknowledge that such a sample may pose challenges regarding the stability and generalizability of machine learning analyses. Using tIVA to integrate multiple data

modalities, we incorporated ICASSO and FastICA to verify the reliability and interpretability of the fused components. While these methodological choices enhanced the robustness of our findings (Langlois et al., 2010), future research would benefit from larger, more diverse samples to validate and expand upon these results. Additionally, the inclusion of both GM and WM components in our study enhances its comprehensiveness; however, we focused solely on structural brain features. Future research could explore the fusion of structural and functional MRI data, such as resting-state or task-related scans, to capture the dynamic brain activity associated with creativity. A multimodal approach would provide a fuller view of both anatomical and functional networks underlying artistic cognition. Another limitation is the operationalization of artistic creativity within a single domain, specifically visual arts. While the focus on professional artists provides valuable insights into neural adaptations associated with visual artistic training, artistic creativity is a multidimensional construct that varies across domains. Future research should consider incorporating other forms of artistic creativity, such as music or dance, to examine both shared and domain-specific neural correlates. Additionally, integrating behavioral assessments and self-report measures could provide a more nuanced understanding of creativity across various forms, contributing to a more holistic model of creative expression.

The use of advanced machine learning and multimodal data fusion in this study highlights the potential for innovative approaches to neuroscience research. Our findings suggest possible implications for clinical applications, as understanding the structural markers of creativity could inform intervention strategies for mental health and neurodegenerative conditions (Acosta, 2014). By continuing to unravel the complex neural networks involved in artistic cognition, neuroscience can deepen our understanding of the interplay between brain structure, creativity, and human experience. This study underscores the essential role of

advanced neuroimaging and data fusion techniques in furthering the field's grasp of creativity and the neural architecture that supports it.

Declarations

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Ethics approval

This study adhered to the ethical standards of the Declaration of Helsinki and was approved by the Ethics Committee of the University of Trento

Consent to participate

Participants provide a signed informed consent to participate to the study

Availability of data and materials

Data will be available upon reasonable request

Author Contributions

ET and AG: methodology, data curation, formal analysis, and writing—original draft preparation, Writing – review & editing.

NDP, DM, FB: conceptualization, data acquisition, Writing – review & editing.

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ANNEX

Table 1.

Independent Component IC-GM 2 Positive Values

Area	Brodmann Area	volume (cc)	random effects: Max Value (x, y, z)
Sub-Gyral	*	2.4/2.5	4.4 (-19, -54, 22)/3.2 (31, 15, 31)
Extra-Nuclear	*	0.3/0.5	4.3 (-16, -53, 19)/2.4 (19, 19, 7)
Middle Frontal Gyrus	9, 10, 46, 47	0.1/4.0	2.1 (-34, -5, 46)/3.8 (37, 18, 31)
Precuneus	7, 31	1.3/0.3	3.6 (-16, -57, 28)/2.7 (22, -77, 27)
Inferior Semi-Lunar Lobule	*	0.6/0.2	3.6 (-15, -82, -38)/2.9 (30, -63, -35)
Posterior Cingulate	29	0.5/0.0	3.6 (-12, -53, 19)/-999.0 (0, 0, 0)
Inferior Parietal Lobule	40	0.7/1.0	3.1 (-40, -56, 40)/3.5 (48, -30, 32)
Fusiform Gyrus	20	1.0/0.8	3.2 (-53, -17, -26)/3.5 (40, -34, -15)
Middle Temporal Gyrus	21	1.5/1.0	3.5 (-52, -14, -8)/2.9 (42, 3, -30)
Pyramis	*	0.5/0.4	3.1 (-22, -86, -32)/3.4 (9, -86, -26)
Angular Gyrus	*	0.2/0.0	3.4 (-39, -56, 36)/-999.0 (0, 0, 0)
Cerebellar Tonsil	*	0.1/1.3	2.1 (-33, -48, -32)/3.4 (31, -59, -35)
Inferior Temporal Gyrus	20, 21	1.8/0.5	3.3 (-53, -20, -22)/3.1 (58, -21, -20)
Precentral Gyrus	9, 44	0.1/0.4	2.5 (-58, 15, 8)/3.2 (37, 21, 34)
Supramarginal Gyrus	40	0.2/0.3	2.6 (-36, -51, 29)/3.2 (46, -51, 23)
Postcentral Gyrus	2	0.0/0.3	-999.0 (0, 0, 0)/3.2 (50, -30, 35)
Superior Temporal Gyrus	21, 22, 41	1.5/0.7	3.2 (-49, -25, 0)/2.8 (49, -51, 21)
Parahippocampal Gyrus	36	0.2/0.0	3.2 (-40, -37, -13)/-999.0 (0, 0, 0)
Tuber	*	0.6/0.1	3.1 (-13, -87, -30)/2.7 (16, -87, -27)
Inferior Frontal Gyrus	10, 44, 45, 46, 47	1.0/1.0	2.7 (-55, 32, -7)/3.1 (55, 38, 1)
Anterior Cingulate	32	0.8/0.3	3.0 (-10, 42, -1)/2.3 (12, 36, 18)
Uvula	*	0.4/0.3	2.6 (-19, -89, -25)/3.0 (13, -87, -25)
Superior Frontal Gyrus	9, 10	0.4/1.5	2.8 (-31, 48, 28)/2.9 (27, 50, 32)
Thalamus	*	1.0/0.5	2.9 (-6, -7, 6)/2.6 (13, -13, 5)
Cuneus	18, 23, 30	0.3/1.3	2.7 (-15, -72, 13)/2.8 (12, -100, 3)
Middle Occipital Gyrus	18	0.0/0.4	-999.0 (0, 0, 0)/2.7 (34, -75, 9)
Transverse Temporal Gyrus	41	0.0/0.4	-999.0 (0, 0, 0)/2.6 (53, -21, 11)
Culmen	*	0.0/0.3	-999.0 (0, 0, 0)/2.5 (9, -39, -14)
Cingulate Gyrus	31, 32	0.3/0.1	2.5 (-10, -19, 34)/2.1 (10, -24, 36)
Lingual Gyrus	17, 18	0.1/0.3	2.3 (-9, -85, -6)/2.4 (13, -98, -5)
Caudate	*	0.3/0.0	2.4 (-16, 15, 12)/-999.0 (0, 0, 0)

Note: (*) = Area not recognized by standard BA atlas.

Table 2.

Independent Component IC-WM 2 Positive Values

Area	**Brodmann Area**	**volume (cc)**	**random effects: Max Value (x, y, z)**
Sub-Gyral	6, 37, 40	3.3/11.1	5.2 (-45, -57, -2)/7.8 (50, -50, -5)
Precuneus	7	1.2/0.6	7.5 (-25, -59, 50)/4.0 (21, -59, 50)
Middle Frontal Gyrus	6, 8, 9, 10, 11, 46	4.5/6.1	6.8 (-33, 18, 43)/7.5 (42, 29, 26)
Precentral Gyrus	4, 6, 9	2.1/7.4	7.3 (-36, 8, 36)/6.7 (52, -11, 35)
Inferior Frontal Gyrus	6, 9, 11, 44, 45	2.2/4.0	4.2 (-40, 24, -10)/7.2 (40, 4, 27)
Inferior Temporal Gyrus	19, 20, 37	1.0/1.4	3.6 (-55, -24, -15)/7.1 (53, -36, -15)
Supramarginal Gyrus	40	1.7/0.1	7.1 (-50, -47, 30)/2.6 (53, -43, 35)
Middle Occipital Gyrus	18	1.8/0.5	6.8 (-28, -89, 3)/4.0 (50, -56, -5)
Postcentral Gyrus	1, 2, 3, 5, 43	1.5/3.7	4.5 (-49, -20, 45)/6.8 (55, -16, 22)
Fusiform Gyrus	20, 37	0.9/0.4	4.0 (-48, -43, -12)/6.4 (50, -37, -12)
Middle Temporal Gyrus	19, 20, 21, 37, 39	5.2/2.8	6.0 (-46, -62, 11)/6.3 (53, -50, -8)
Cerebellar Tonsil	*	5.2/5.8	5.3 (-24, -51, -33)/5.9 (24, -50, -32)
Inferior Parietal Lobule	7, 39, 40	1.5/1.3	4.8 (-50, -36, 42)/5.7 (40, -56, 47)
Pyramis	*	1.9/1.8	4.6 (-21, -63, -28)/5.4 (21, -60, -30)
Superior Parietal Lobule	7	0.8/0.6	5.3 (-25, -57, 46)/3.2 (21, -60, 54)
Cuneus	17, 18, 19	2.9/1.0	5.3 (-19, -88, 20)/4.0 (13, -79, 23)
Culmen	*	4.6/5.1	4.7 (-22, -55, -26)/5.1 (24, -55, -26)
Fastigium	*	0.4/0.4	4.8 (-10, -51, -20)/3.8 (10, -52, -19)
Nodule	*	0.4/0.3	4.7 (-13, -51, -29)/3.2 (10, -64, -23)
Uvula	*	1.0/1.3	3.6 (-16, -67, -26)/4.6 (15, -60, -30)
Superior Temporal Gyrus	13, 22, 39	0.4/0.1	4.4 (-52, -52, 10)/2.8 (42, -20, 9)
Medial Frontal Gyrus	10	1.2/0.6	4.3 (-10, 53, 8)/2.8 (9, 59, 12)
Superior Frontal Gyrus	8, 9	0.6/0.7	3.7 (-24, 46, 9)/4.2 (24, 53, 10)
Extra-Nuclear	*	1.6/3.3	4.1 (-1, 17, 16)/3.7 (33, -9, 25)
Cerebellar Lingual	*	0.2/0.0	3.8 (-7, -49, -18)/-999.0 (0, 0, 0)
Declive	*	0.6/2.0	3.6 (-1, -55, -14)/3.0 (12, -71, -22)
Insula	*	0.0/0.2	-999.0 (0, 0, 0)/3.0 (45, -17, 8)
Inferior Semi-Lunar Lobule	*	0.4/0.3	2.5 (-15, -63, -35)/2.9 (22, -64, -36)
Parahippocampal Gyrus	*	0.1/0.2	2.2 (-24, -48, 4)/2.8 (33, -16, -23)
Cingulate Gyrus	*	0.4/0.0	2.8 (-7, 12, 27)/-999.0 (0, 0, 0)

Note: (*) = Area not recognized by standard BA atlas

Table 3.

Independent Component IC-GM 8 Positive Values

Area	**Brodmann Area**	**volume (cc)**	**random effects: Max Value (x, y, z)**
Inferior Semi-Lunar Lobule	*	2.0/2.9	3.5 (-28, -75, -40)/4.8 (33, -76, -40)
Lateral Ventricle	*	0.3/1.4	3.1 (-36, -18, -14)/4.6 (24, -48, 9)
Pyramis	*	0.7/1.2	3.6 (-27, -83, -31)/4.5 (31, -83, -34)
Extra-Nuclear	*	0.3/2.2	2.6 (-4, 26, -1)/4.2 (24, -50, 12)
Tuber	*	1.0/1.9	3.3 (-25, -86, -29)/4.2 (33, -85, -30)
Middle Occipital Gyrus	19	1.7/1.4	3.9 (-34, -78, 5)/3.6 (28, -81, 15)
Uvula	*	0.4/0.6	3.0 (-25, -86, -25)/3.9 (31, -86, -26)
Cerebellar Tonsil	*	2.3/0.2	3.9 (-43, -49, -40)/2.7 (43, -59, -41)
Middle Frontal Gyrus	6, 10, 11	0.8/0.4	3.8 (-24, 5, 44)/2.7 (33, 26, 29)
Lingual Gyrus	17, 18	1.3/0.2	3.8 (-6, -97, -9)/2.9 (1, -88, -9)
Inferior Frontal Gyrus	*	0.3/0.2	3.7 (-34, 6, 26)/2.7 (34, 29, 1)
Superior Temporal Gyrus	22, 38, 39	0.9/0.8	3.5 (-45, -53, 10)/3.0 (48, -44, 15)
Middle Temporal Gyrus	21, 22, 38, 39	1.1/1.4	3.5 (-48, -52, 7)/3.0 (52, -47, -1)
Anterior Cingulate	24, 32	0.9/0.6	3.5 (-1, 26, -4)/3.0 (1, 23, -4)
Declive	*	0.5/1.0	2.9 (-31, -84, -21)/3.5 (27, -88, -20)
Sub-Gyral	20	2.6/1.8	3.5 (-31, -60, 33)/3.1 (43, -25, 25)
Inferior Occipital Gyrus	18	0.0/0.3	-999.0 (0, 0, 0)/2.9 (27, -90, -14)
Parahippocampal Gyrus	30	1.3/0.9	2.8 (-33, -15, -14)/2.9 (19, -42, 5)
Medial Frontal Gyrus	9	0.0/0.4	-999.0 (0, 0, 0)/2.6 (10, 38, 26)
Angular Gyrus	39	0.2/0.0	2.5 (-37, -63, 31)/-999.0 (0, 0, 0)
Cingulate Gyrus	*	0.1/0.3	2.3 (-9, -33, 35)/2.4 (7, 14, 27)

Note: (*) = Area not recognized by standard BA atlas

Table 4.

Independent Component IC-WM 8 Positive Values

Area	**Brodmann Area**	**volume (cc)**	**random effects: Max Value (x, y, z)**
Middle Occipital Gyrus	18, 19	4.5/4.4	6.3 (-30, -79, 21)/9.4 (45, -63, -3)
Inferior Parietal Lobule	7, 40	0.1/2.3	3.5 (-30, -52, 43)/8.4 (36, -55, 41)
Sub-Gyral	3, 20, 39, 40	21.7/22.1	5.8 (-34, -13, -25)/7.9 (42, -60, -2)
Superior Parietal Lobule	5, 7	1.0/1.3	7.4 (-25, -56, 47)/6.2 (31, -55, 43)
Lingual Gyrus	17, 18, 19, 30	6.5/7.6	5.5 (-15, -87, 4)/7.3 (21, -57, 3)
Angular Gyrus	*	0.4/0.3	2.8 (-37, -71, 31)/6.7 (37, -53, 37)
Parahippocampal Gyrus	18, 19, 30, 35, 37	2.0/2.0	6.5 (-34, -16, -22)/5.5 (25, -55, 3)
Posterior Cingulate	23, 30, 31	1.3/3.1	3.7 (-10, -65, 10)/6.2 (18, -58, 6)
Cuneus	7, 17, 18, 19, 23, 30	11.8/9.7	6.0 (-15, -84, 7)/6.0 (7, -73, 16)
Middle Frontal Gyrus	6, 8, 9, 10, 11, 46	4.1/7.6	5.9 (-37, 30, 23)/5.7 (36, 12, 44)
Precuneus	7, 19, 31	3.1/5.2	5.8 (-28, -54, 50)/5.1 (24, -47, 47)
Medial Frontal Gyrus	6, 9, 10, 11, 32	5.1/8.8	4.5 (-18, 44, 13)/5.8 (12, 59, 5)
Supramarginal Gyrus	*	0.1/1.0	2.3 (-36, -50, 26)/5.7 (34, -51, 36)
Middle Temporal Gyrus	19, 21, 22, 37, 39	4.5/2.7	5.5 (-33, -79, 23)/5.0 (45, -60, 0)
Inferior Temporal Gyrus	19, 20, 37	1.1/0.4	4.4 (-49, -20, -22)/5.4 (48, -63, -1)
Fusiform Gyrus	19, 20, 37	3.1/0.3	5.3 (-49, -17, -24)/2.7 (43, -49, -13)
Superior Frontal Gyrus	6, 8, 10, 11	2.8/4.5	3.8 (-13, 50, -13)/4.7 (12, 47, -15)
Precentral Gyrus	6, 9, 43, 44	2.4/2.7	4.5 (-31, -11, 52)/4.3 (39, 3, 29)
Anterior Cingulate	9, 10, 32	2.4/0.4	4.5 (-12, 36, 24)/3.4 (18, 43, 8)
Inferior Occipital Gyrus	17, 18	0.8/0.6	4.2 (-31, -76, -3)/3.8 (31, -82, -3)
Cingulate Gyrus	24, 31, 32	1.1/1.6	3.4 (-10, -39, 42)/4.1 (7, -41, 30)
Superior Temporal Gyrus	22, 39	0.6/0.2	3.7 (-48, -59, 20)/2.6 (53, -51, 21)
Inferior Frontal Gyrus	9, 13, 44, 45, 47	1.7/1.5	3.4 (-40, 24, 11)/3.6 (40, 6, 31)

Note: (*) = Area not recognized by standard BA atlas.
Inside each component, the brain areas are ordered according to the GIFT Toolbox output settings. tIVA-2 and tIVA-8, negative values for both GM and WM were not reported. Only positive areas with a volume of 0.2> are reported in the tables. Also, note that significant WM portions are reported in this table by considering their adjacencies with GM regions