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Reduced GM–WM concentration inside the Default Mode Network in individuals with high emotional intelligence and low anxiety: a data fusion mCCA+jICA approach

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Abstract

The concept of emotional intelligence (EI) refers to the ability to recognize and regulate emotions to appropriately guide cognition and behaviour. Unfortunately, studies on the neural bases of EI are scant, and no study so far has exhaustively investigated grey matter (GM) and white matter (WM) contributions to it. To fill this gap, we analysed trait measure of EI and structural MRI data from 128 healthy participants to shed new light on where and how EI is encoded in the brain. In addition, we explored the relationship between the neural substrates of trait EI and trait anxiety. A data fusion unsupervised machine learning approach (mCCA + jICA) was used to decompose the brain into covarying GM–WM networks and to assess their association with trait-EI. Results showed that high levels trait-EI are associated with decrease in GM–WM concentration in a network spanning from frontal to parietal and temporal regions, among which insula, cingulate, parahippocampal gyrus, cuneus and precuneus. Interestingly, we also found that the higher the GM–WM concentration in the same network, the higher the trait anxiety. These findings encouragingly highlight the neural substrates of trait EI and their relationship with anxiety. The network is discussed considering its overlaps with the Default Mode Network.

Keywords: emotional intelligence; anxiety; independent component analysis (ICA); neuroimaging; machine learning

Introduction

The concept of emotional intelligence (EI) comprises a number of personality traits and competencies that involve the ability to perceive, understand, regulate and harness emotions adaptively in the self and in others (Salovey and Mayer, 1990; Zanella *et al.*, 2022; Ghomroudi *et al.*, 2023; Monachesi *et al.*, 2023). In this sense, an emotionally intelligent individual can be described as a person who is effective in utilizing emotional signals to guide behaviours appropriately and advantageously. Large meta-analytic evidence has shown clear associations between EI and mental/general health indicators (Schutte *et al.*, 2007; Martins *et al.*, 2010), subjective well-being (Sánchez-Álvarez *et al.*, 2016; Xu *et al.*, 2021), adaptive emotion regulation (Zanella *et al.*, 2022), better relationships (Malouff *et al.*, 2014; Walker *et al.*, 2022) and academic/work achievements (O'Boyle *et al.*, 2011; MacCann *et al.*, 2020; Sánchez-Álvarez *et al.*, 2020). Despite the large documentation on various social, cognitive and interpersonal outcomes related to EI, the empirical validity of the concept is still debated and an exhausted description of the neural processes that may underpin the construct is frequently mentioned as missing point in the determination of EI construct validity (Waterhouse, 2006; Humphrey *et al.*, 2007; Tarasuik *et al.*, 2009). The present study sought to provide new and more exhaustive knowledge on the neurocircuit underlying the EI for its better neurobiological conceptualization.

In literature, there are leading theories of EI conceiving the construct in terms of trait or abilities (e.g. Webb *et al.*, 2013). In the present study, we focused on trait EI since it represents an individual's predisposition measure, which is involved in person's behaviours and intents (Zanella *et al.*, 2022), but it does not overlap with general cognitive functions as the ability EI mostly does. Indeed, the continued reflexive process on emotional experience and its integration with goal-directed behaviours, which characterize EI (Salovey and Mayer, 1990), should be reflected not only in the involvement of purely executive functions, but also and above all brain structures involved in the coordination of social and affective systems. In this sense, there is evidence of brain characteristics underlying EI and involving both white matter (WM)

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and grey matter (GM). For example, voxel-based morphometry (VBM) studies have reported significant correlations between individual differences in EI and GM volume/density in areas such as the orbito-frontal cortex (OFC) and the insula and temporal lobe (Koven et al., 2011; Takeuchi et al., 2011; Weber et al., 2013; Tan et al., 2014; He et al., 2018). In addition, intra- and inter-personal aspects of EI have been reported as positively correlated with WM integrity in the right anterior insula, and in a part of the right inferior longitudinal fasciculus (ILF), respectively (Takeuchi et al., 2013).

The literature offers several, compatible hypotheses for the interpretation of these data. A first hypothesis is based on the 'somatic marker' theory (Damasio, 1996). According to this hypothesis, the core of EI is the ability of integrating sensory and visceral bodily information, localized in the orbitofrontal/ventromedial prefrontal and insula areas of the brain. A second hypothesis empathizes the importance of social skills in EI. This hypothesis is in line with the detection of areas in Social Cognitive Network, such as the temporal lobes (Yao et al., 2018) and the ILF in association to EI (Takeuchi et al., 2013). In the present study, we consider also a third, less explored, hypothesis which considers the possible role of the Default Mode Network (DMN) in EI. The DMN is made up of functional hubs: the medial prefrontal cortex, the posterior cingulate cortex, precuneus and the angular gyrus (Andrews-Hanna et al., 2014). Neuroimaging studies have recently shown that the DMN is largely implied in anxiety (Saviola et al., 2020; Baggio et al., 2023), borderline personality (Grecucci et al., 2022; Langerbeck et al., 2023), narcissistic personality (Jornkokgoud et al., 2023), negative affectivity (Ghomroudi et al., 2023), anger expression problems (Sorella et al., 2022; Grecucci et al., 2023a), rumination (Zhou et al., 2020) and general psychopathology (Coutinho et al., 2016; Messina et al., 2016). All this evidence converges toward the direction of the DMN as being implied in many if not all mental disorders. In contrast, previous behavioural studies have reported overthinking, rumination as well as decreased anxiety, emotional reactivity and impulsivity in individuals with high EI (Kauts and Saroj, 2010; Zanella et al., 2022). Indeed, EI is associated with higher subjective well-being (Sánchez-Álvarez et al., 2016; Xu et al., 2021) and more adaptive emotion regulation (Zanella et al., 2022). If it is true that the DMN is positively associated with psychological problems, and EI is negatively associated with psychological problems, we expect EI to be negatively correlated with the DMN. In other words, we expect that individuals with higher EI will exhibit decreased GM–WM concentration in regions of the DMN linked to processes like rumination, overthinking, emotional reactivity and anxiety (Baggio et al., 2023). These areas have also been associated with borderline and narcissistic personality disorders (Grecucci et al., 2022; Jornkokgoud et al., 2023; Langerbeck et al., 2023). Moreover, based on the evidence that higher the EI, the lower the anxiety, we also expect the reduced GM–WM concentration inside the DMN to be also associated with anxiety but in an opposite direction.

Considering the absence of an integral and comprehensive neurobiological model of EI, in the present study, we opted for a methodological approach coherent with a network perspective, which allows the study of emotional processes as distributed across a subset of regions (Hamann, 2012). To this aim, we adopted a multimodal canonical correlation analysis with joint independent component analysis (mCCA-jICA; Sui et al., 2013). This approach is based on decomposing the cortex into naturally grouping networks, based on covarying GM and WM concentrations. Generally, this approach can firstly find maximally correlated components between multiple modalities (mCCA), and then to decompose these correlated components into spatially independent components (jICA). The mCCA-jICA has been already successfully applied to investigate covarying GM and WM concentration in the context of cognitive decline and mild cognitive impairment (Ling et al., 2019), anxiety (Baggio et al., 2023) and obsessive-compulsive disorder (Kim et al., 2015). Here, it is employed to reveal those independent components of covarying GM and WM concentration associated with the trait EI. Note that previous studies of EI provided promising attempts in describing neural basis of EI in terms of WM and GM features. However, they investigated the neural underpinnings of EI focusing only on one measurement of the brain characteristics or both but separately (Takeuchi et al., 2011, 2013).

The advantages of this approach are multiple. Independent component analysis (ICA) applied to structural brain features (i.e. source-based morphometry, (Xu et al., 2009) is an unsupervised machine learning multivariate method that considers the statistical dependency among voxels. Based on regions with covarying GM and WM concentration, the brain is decomposed into naturally grouping networks with lower and consistent dimensionality (Kim et al., 2015; Grecucci et al., 2023b). This has the advantage of avoiding a priori atlas-defined regions (ROIs) and biologically implausible portions of the brain (e.g. spheres cantered on coordinates). Constraining the effect of interest on such arbitrary partitions may be in fact misleading (Sorella et al., 2022; Baggio et al., 2023; Grecucci et al., 2023b). Finally, an approach based on decomposing the cortex into naturally grouping networks (based on covarying GM and WM concentrations) is also more coherent with a network perspective in neuroscience (Hamann, 2012), building upon the notion that emotional processes are distributed across a subset of regions constituting a network.

Methods

Participants

Brain scans and questionnaire scores of 128 German-speaker participants (36 Females, mean age 29.72, SD = 12.43; years of education mean: 12.73, SD = 0.87) were included in the present study. The data were selected from 'Leipzig study for mind-body-emotion interactions' OpenNeuro database (accession number ds000221) (LEMON, Babayan et al., 2019), the collection of which was conducted at the Max Planck Institute for Human Cognitive and Brain Sciences (MPI CBS) in Leipzig (Germany), between 2013 and 2015. Participants were selected based on medical eligibility for magnetic resonance sessions and the absence of past or present psychiatric and neurological disorders. All participants provided written informed consent prior to the data collection, and they received a compensation after the completion of all assessments. In the present study, further inclusion criteria for the extracted subset of participants were a negative drug test, no excessive alcohol use and a negative diagnosis at the SCID-I for a psychopathological screening (information retrieved in Babayan et al., 2019). For each participant, we extracted structural MRI scans (T1 Weighted—MP2RAGE) and the measure of trait EI and trait anxiety. Namely, we selected the scores of German version of the Trait EI Questionnaire Short-Form (TEIQue—SF, Petrides, 2009), one of the most widely used measures. TEIQue—SF, developed by Petrides (2009), conceptualizes EI as a personality trait and provides a comprehensive operationalization of trait EI theory. The questionnaire, administered in the German validated version, assesses four factors: (i) well-being ($\alpha = 0.94$), (ii) self-control ($\alpha = 0.86$), (iii) emotionality ($\alpha = 0.90$), (iv) sociability

($\alpha = 0.88$), and a total trait EI index ($\alpha = 0.96$). The German version demonstrated good model fit reliability ($\chi 2$ (54, $N = 352$) = 147.78, CFI = 0.95, SRMR = 0.049 and RMSEA = 0.07), and the test validity was reliable ($0.88 \leq \alpha \leq 0.96$) (Babayan et al., 2019). TEIQue—SF comprises 26 items across the four factors: well-being (6 items), self-control (6 items), emotionality (8 items) and sociability (6 items), along with four items contributing to the total trait EI index score. Responses are recorded on a 7-point Likert scale (1 to 7, from 'completely disagree' to 'completely agree'). The total trait EI index score is computed by dividing the sum of items scores by the total number of items. For this study, we included in the analysis only the total trait EI index as an exhaustive and complete measure of the EI construct, and to avoid redundancy in the analysis. The descriptive statistics for the total trait EI index ($N = 128$) were $M = 154.29$ and $SD = 17.44$ (max value = 195; min value = 103). Note that we used the sum of scores, as reported in the Lemon dataset, and not the average. Although there are no established norms for TEIQue-SF, when considering the average of scales, our sample perfectly aligns with the values reported in the original validation study by Cooper and Petrides (2010) (M = 5.143, our sample; M = 5.1, the original study). In addition, we selected the scores of the German version of the State-Trait Anxiety Inventory (Laux et al., 1981) to assess the anxiety trait. It consists of 20 items, with a 4-point Likert scale ranging from

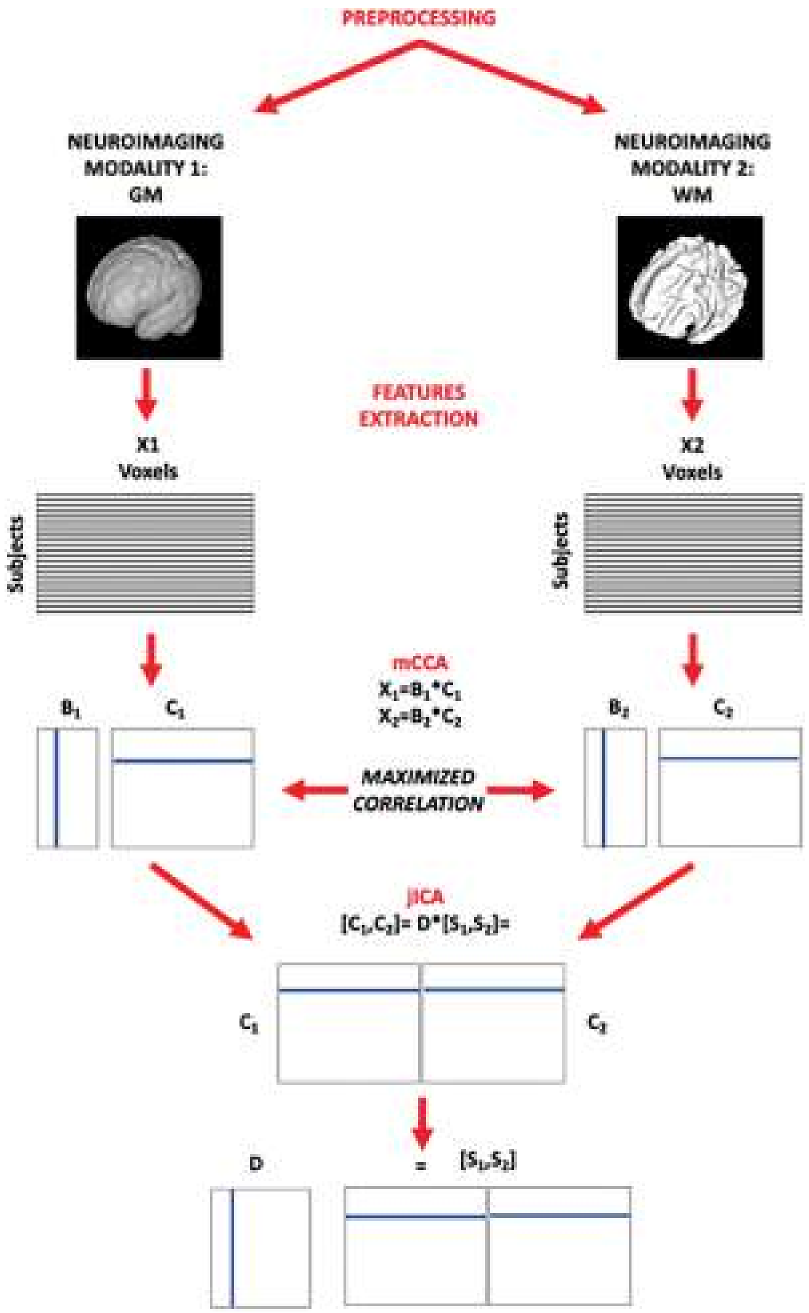

Fig. 1. Diagram of the mCCA + jICA method. First, the structural T1 images were pre-processed and the features of two neuroimaging modalities (GM and WM) were extracted and reorganized into two matrices, X1 and X2. After dimensionality reduction, mCCA was applied to X1 and X2, and the canonical variants B1 and B2 as well as the associated components C1 and C2 were computed. Then, jICA was applied to C1 and C2 to compute the maximized joint-independent component matrices S1 and S2 (sources) and the relative loading coefficients mixing matrix D. The loading coefficients were then used for predicting EI and additional analyses.

1 (almost never) to 4 (nearly always). The descriptive statistics for the anxiety were $M = 36.98$ and $SD = 8.19$ (max value = 57; min value = 21). According to the developer (Spielberger *et al.*, 1983), our sample falls within the moderate anxiety level. Indeed, the defined ranges classify scores of 20–39 as low anxiety, 40–59 as moderate anxiety and 60–80 as high anxiety. The validity and reliability values for the German version of the two scales as well as the internal consistency (Cronbach's α) for the whole sample in the original dataset are reported in the study of Babayan *et al.* (2019).

Image acquisition

For Structural images acquisition, a 3 Tesla scanner (MAGNETOM Verio, Siemens Healthcare GmbH, Erlangen, Germany) equipped with a 32-channel head coil was used. T1-weighted structural volumes were acquired using MP2RAGE sequence (TR = 5000 ms, TE = 2.92 ms, TI1 = 700 ms, TI2 = 2500 ms, FOV = 256 mm, voxel size = 1 mm isotropic), and with 176 slices interspersed during 8 min 22 s of scanning. During the acquisition, participants were asked to stay awake and look at a low-contrast fixation cross.

Data analysis

Pre-processing

Structural MRI data have been firstly assessed for its quality in order to exclude any possible scanning artefacts. Then, the pre-processing was conducted using Computational Anatomy Toolbox (CAT12, http://www. neuro.uni-jena.de/cat/), a toolbox for statistical Parametric Mapping (SPM12, http://www.fil.ion.ucl.ac.uk/spm/software) in MATLAB environment (https://it.mathworks.com/products/matlab.html). The structural images were manually reoriented to the anterior commissure as the origin, and then segmented into GM, WM and cerebrospinal fluid (CSF). The GM image registration was conducted with Diffeomorphic Anatomical Registration using Exponential Lie algebra (DARTEL) tools for SPM12 (https://github.com/scanUCLA/spm12-dartel, Komatsu *et al.*, 2018). Finally, the DARTEL images were normalized to MNI-152 standard space and each image was smoothed with a 12 mm full-width at half-maximum (FWHM) Gaussian kernel [12, 12, 12].

Data fusion unsupervised machine learning

For the network decomposition, the mCCA + jICA was applied to structural data using the Fusion ICA Toolbox (FIT, http://mialab.mrn.org/software/fit, Calhoun *et al.*, 2009) in the MATLAB 2018 environment. The dimensionality of both GM and WM features was reduced using singular value decomposition (SVD) for each modality retaining more than 98.9% of non-zero eigenvalues of both modalities. A modified Akaike's information criterion (AIC, Akaike, 1974; Li *et al.*, 2009) was used to estimate the number of joint sources, k, from matrix X (Calhoun *et al.*, 2001).

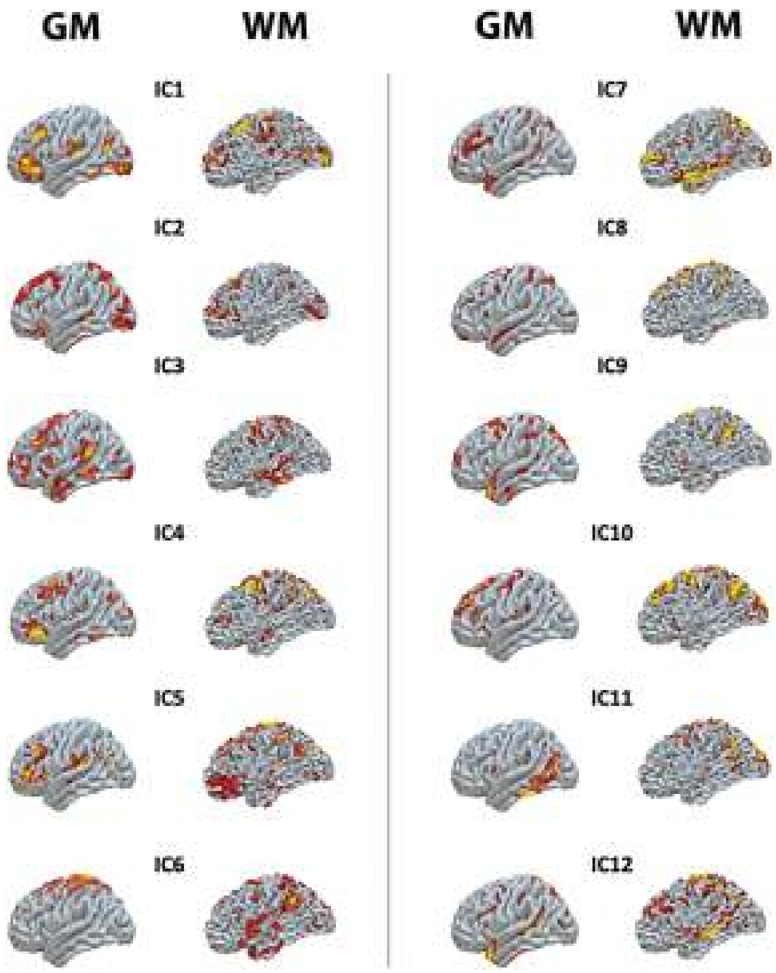

Fig. 2. Independent covarying GM–WM networks. mCCA + jICA was able to decompose the brain into 12 covarying GM–WM networks. Only the positive tail of the distribution is plotted.

The mCCA served to separate the reduced features by the mixing profiles and the associated components (Sui *et al.*, 2013). The canonical variates represent the contribution of the associated component to the features of the individual subjects. The correlation of canonical variates was maximized step-wisely from the first to the last associated component, while the correlation between the canonical covariates with different indices was minimized. Then, the jICA was applied to decompose the matrix into independent networks. The jICA is a data fusion method which can combine multiple types of data from the same participants and extract their correlated information (Calhoun *et al.*, 2009). The joint sources are maximally and spatially independent and each corresponds to a set of GM regions and a set of WM regions. GM shares the same contribution to the intersubject covariation and hence capture the linked GM and WM group differences (Xu *et al.*, 2009). This was done as the components found using mCCA typically contain sources that are not independent due to the spatial dependency of neuroimaging data across modalities. The statistical dependency among the joint independent components was minimized via information maximization (Calhoun *et al.*, 2009). See Figure 1 for an outline of the method.

Infomax algorithm was used to separate independent sources, which performs optimally under the assumption of super-Gaussianess. To increase stability of the non-linear optimization, jICA was performed for 100 times. Results were plotted via Surf Ice (https://www.nitrc.org/projects/surfice/).

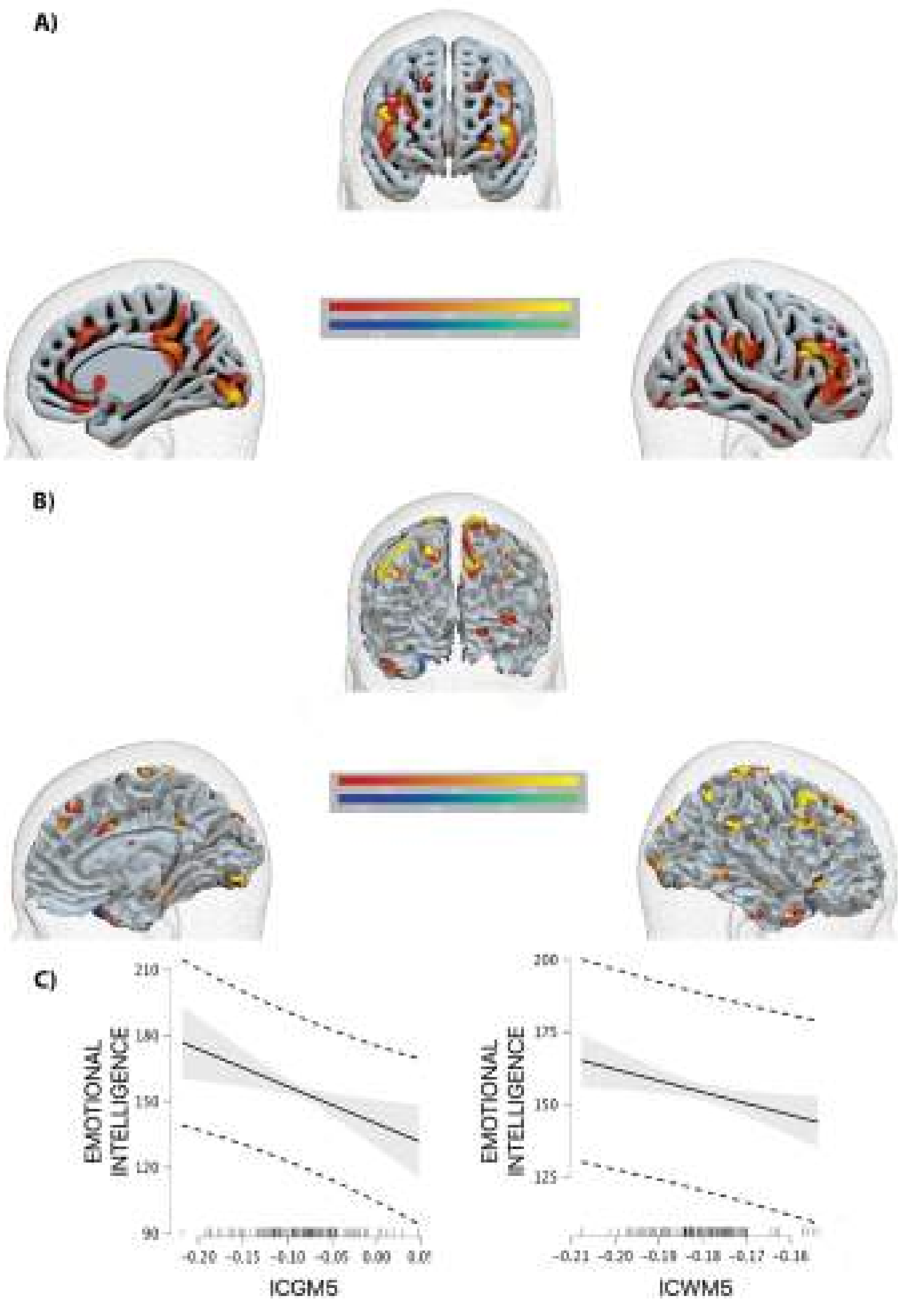

Fig. 3. Visual representation of ICGM5 and ICWM5 and their association with trait EI. (A) Brain plots of ICGM5 and (B) ICWM5. The red and the blue colours in the brain plots represent positive and negative correlational values, respectively. (C) Plot of the regression between EI (i.e. total trait EI index score of TEIQue-SF) and ICGM5 (on the left) and ICWM5 (on the right). Marginal effect in the regression is also displayed at the bottom of the chart.

Covarying GM–WM components associated with EI and anxiety

By performing the mCCA-jICA analysis, the brain was decomposed into independent covarying GM–WM components. Covarying components means that these two types of features for the two modalities are correlated with each other, and that they are concatenated and decomposed together when performing mCCA-jICA. However, the correlation between the ICs of the GM and WM does not necessarily imply that both these two modalities correlate in turn with the psychological construct of interest (trait EI). Therefore, to verify that, the loading coefficients of every IC were entered in a backward regression for WM and GM, separately, and the total trait-EI was entered as the dependent variable (see Liang *et al.*, 2021, for similar procedure). To control for the eventual effects of age and gender, we included them in the two stepwise regressions. Only those components associated with trait EI for both modalities will be discussed as the joint independent components underlying the psychological construct (Liang *et al.*, 2021). JASP (Version 0.16) was used to perform the analyses.

To assess the relationship between EI and anxiety, and then between anxiety and the neural networks involved in EI, we computed a Spearman correlation controlling for age and gender. All correlations were Bonferroni corrected.

Results

Networks decomposition

The information theoretic criteria estimated 12 independent covarying GM (ICGM) and WM (ICWM) components. The values of these components refer to the increased GM–WM concentration. The meaning of the covariation between a GM and a WM component refers to a similar pattern of GM–WM concentration. The brain regions involved in the WM networks have to be interpreted as regions of WM tracts that pass nearby and across the resulted named areas. See Figure 2 for details of the ICs.

Neural prediction

For what concerns GM networks, multiple linear regression using backward data entry returned that a model including ICGM5 (*beta* = −169.452, $P = 0.007$) and ICGM10 (*beta* = −182.868, $P = 0.01$) were successfully and negatively associated with EI. Similarly, for WM analysis, the multiple linear regression using backward data entry again returned that a model including ICWM5 (beta = −394.571, $P = 0.014$) was successfully and negatively associated with EI. ICGM5 and ICWM5 were highly correlated (Pearson $r = 0.497$, $P < 0.001$). Of note, the effects of age and gender were not significant in the winning models of both the stepwise regressions. The regions of GM and WM involved in the IC5 were spanning

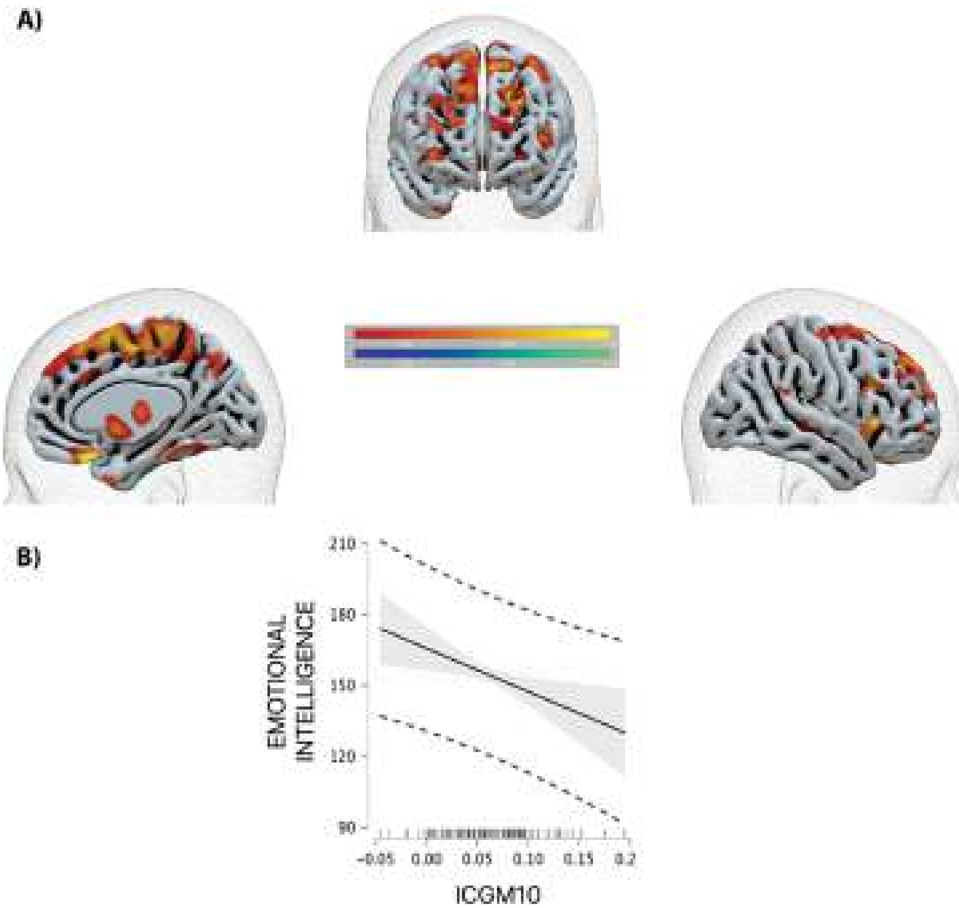

Fig. 4. Visual representation of ICGM10 and its association with trait EI. (A) Brain plots of ICGM10. The red and the blue colours in the brain plots represent positive and negative correlational values, respectively. (B) Plot of the regression between EI (i.e. total trait EI index score of TEIQue-SF) and ICGM10. Marginal effect in the regression is also displayed at the bottom of the chart.

Table 1. Grey matter (GM) and white matter (WM) regions included in IC5 (threshold = 4). BA = Brodmann Areas.

Area	BA	Volume (cc)	Random effects: max value (x, y, z)
ICGM5			
Middle Frontal Gyrus	9, 10, 46	2.9/2.2	5.4 (−36, 26, 33)/10.9 (43, 20, 22)
Sub-Gyral	*	0.6/2.6	6.2 (−40, 40, 4)/9.5 (40, 17, 23)
Inferior Frontal Gyrus	9, 10, 45, 46, 47	2.0/2.2	6.0 (−42, 37, 6)/7.4 (49, 23, 20)
Lingual Gyrus	17, 18	1.2/1.7	6.3 (−3, −89, −9)/6.6 (1, −88, −8)
Superior Temporal Gyrus	41	0.6/0.0	5.9 (−40, −30, 17)/ −999.0 (0, 0, 0)
Middle Temporal Gyrus	*	0.8/0.0	5.8 (−40, −64, 23)/ −999.0 (0, 0, 0)
Inferior Parietal Lobule	7, 39, 40	1.2/2.1	5.6 (−50, −37, 24)/5.5 (52, −26, 26)
Insula	13, 41	1.9/0.3	5.5 (−43, −31, 20)/4.5 (49, −24, 21)
Inferior Occipital Gyrus	17	0.1/0.1	5.0 (−10, −92, −9)/4.2 (16, −91, −8)
Supramarginal Gyrus	40	0.4/0.1	5.0 (−52, −45, 26)/4.1 (59, −38, 30)
Superior Parietal Lobule	7	0.0/0.4	−999.0 (0, 0, 0)/5.0 (30, −58, 43)
Transverse Temporal Gyrus	41	0.3/0.0	5.0 (−40, −30, 11)/ −999.0 (0, 0, 0)
Precentral Gyrus	9	0.1/0.0	4.8 (−36, 24, 36)/ −999.0 (0, 0, 0)
Cingulate Gyrus	31	0.0/0.5	−999.0 (0, 0, 0)/4.8 (7, −41, 32)
Cerebellar Tonsil	*	0.0/0.4	−999.0 (0, 0, 0)/4.6 (33, −50, −40)
Cuneus	18	0.1/0.0	4.6 (−3, −93, 0)/ −999.0 (0, 0, 0)
Precuneus	19	0.0/0.4	−999.0 (0, 0, 0)/4.5 (30, −62, 40)
Angular Gyrus	*	0.1/0.1	4.4 (−40, −65, 31)/4.2 (42, −65, 32)
ICWM5			
Sub-Gyral	*	0.1/1.9	4.2 (−10, −21, 47)/7.6 (43, 11, 17)
Precentral Gyrus	4, 9	0.0/0.5	−999.0 (0, 0, 0)/6.9 (34, 13, 34)
Medial Frontal Gyrus	6	1.1/0.0	6.0 (−7, −10, 53)/ −999.0 (0, 0, 0)
Middle Frontal Gyrus	*	0.0/0.4	−999.0 (0, 0, 0)/5.6 (37, 13, 31)
Lingual Gyrus	18	0.5/0.0	5.4 (−12, −77, −1)/ −999.0 (0, 0, 0)
Inferior Parietal Lobule	40	0.4/0.1	5.0 (−43, −34, 40)/4.4 (43, −50, 40)
Postcentral Gyrus	3, 4	0.0/0.3	−999.0 (0, 0, 0)/4.7 (22, −29, 53)
Superior Frontal Gyrus	*	0.0/0.1	−999.0 (0, 0, 0)/4.4 (19, 34, 33)
Paracentral Lobule	6	0.2/0.0	4.3 (−7, −18, 47)/ −999.0 (0, 0, 0)
Inferior Frontal Gyrus	*	0.0/0.1	−999.0 (0, 0, 0)/4.0 (37, 10, 29)

(*) = area not recognized by standard BA atlas.

from frontal to parietal and temporal lobes, including insula, cingulate, fusiform, parahippocampal gyrus, cuneus and precuneus (Figure 3).

The areas of GM involved in the ICGM10 were mainly the caudate, frontal regions and the middle-inferior temporal area (see Figure 4). Of note, both networks—especially IC5—overlap with the Default Mode Network (see Supplementary material for a visual comparison). For a detailed list of all areas involved in IC5 and ICGM10, see Tables 1 and 2. Areas for ICWM10 are reported in the Supplementary material.

Additional analyses

To assess the relationship between EI and anxiety, and then between anxiety and the loading coefficients of ICGM5 and ICWM5, we computed a Spearman correlation with a corrected Bonferroni threshold of 0.0125, controlling for age and gender. Spearman correlation was preferred to Pearson correlation as anxiety was not normally distributed as the results at the Wilk-Shapiro test showed ($W(128) = 0.98$, $P = 0.04$), differently from all other variables ($P > 0.06$). As expected, EI was significantly and negatively correlated with anxiety ($\rho = -0.511$, $P < 0.001$). Moreover, anxiety significantly and positively correlated with both ICGM5 ($\rho = 0.227$, $P = 0.011$) and with ICWM5 ($\rho = 0.282$, $P = 0.001$) (see Figure 5). To further rule out the effect of gender on EI, we directly ran a simple independent t-test that returned to be not significant ($t(1126) = 0.164$, $P = 0.870$). In addition, to further rule out the effect of age on EI, we ran a Pearson correlation that returned to be not significant as well ($r = -0.005$, $P = 0.952$).

Table 2. Grey matter (GM) regions included in IC10 (threshold = 4.5). BA = Brodmann Areas.

Area	BA	Volume (cc)	Random effects: max value (x, y, z)
Rectal Gyrus	11	0.3/0.3	5.3 (−6, 18, −25)/5.8 (3, 23, −26)
Caudate	*	0.5/0.0	4.7 (−12, 14, 9)/ −999.0 (0, 0, 0)
Sub-Gyral	*	0.0/0.1	−999.0 (0, 0, 0)/4.4 (42, 19, 23)
Superior Frontal Gyrus	6, 9	0.1/0.2	4.3 (−22, 44, 32)/4.3 (10, 10, 58)
Medial Frontal Gyrus	6	0.1/0.0	4.1 (−3, −22, 62)/ −999.0 (0, 0, 0)
Middle Frontal Gyrus	8	0.1/0.0	4.1 (−24, 25, 40)/ −999.0 (0, 0, 0)
Tuber	*	0.0/0.1	−999.0 (0, 0, 0)/4.1 (36, −58, −30)
Lentiform Nucleus	*	0.0/0.1	−999.0 (0, 0, 0)/4.0 (18, 3, −3)
Culmen	*	0.0/0.1	−999.0 (0, 0, 0)/4.0 (24, −35, −22)

(*) = area not recognized by standard BA atlas.

Discussion

A still debated issue for the determination of EI construct validity is the description of its neural correlates. So far, several studies approached the topic focusing on brain structural features asso-

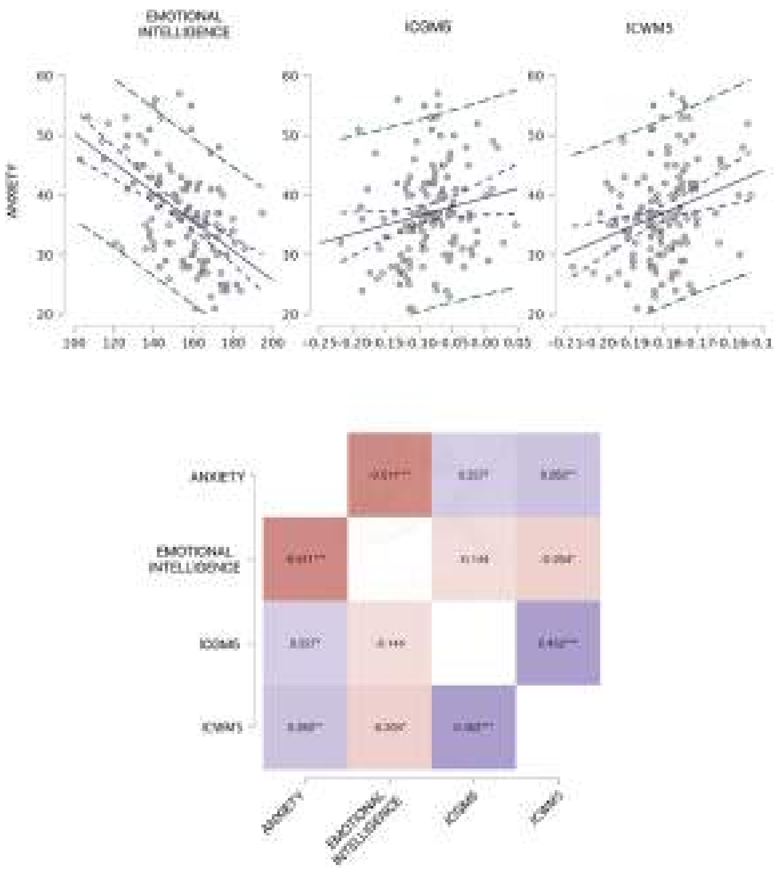

Fig. 5. Correlations between EI, anxiety and loading coefficients of ICGM5, ICWM5, ICGM10. Top of the panel: correlations density plot between EI (i.e. total trait EI index score of TEIQue-SF), Anxiety (ANX trait), and the loading coefficients of ICGM5 and ICWM5. Anxiety is significantly and negatively correlated with EI, and positively correlated with ICGM5 and ICWM5. Bottom of the panel: heatmap of correlations.

ciated with EI, and emphasizing WM or GM features, separately. The present study, instead, is aimed at investigating the neural characteristics associated with trait EI by using the advanced and promising unsupervised machine learning approach known as mCCA-jICA, which is able to reveal the covarying concentration of both WM and GM at once.

Results of our study firstly identified 12 independent covarying GM and WM networks. Especially, the loading coefficients of one GM–WM component (IC5) was found to be significantly and negatively correlated with trait EI total index. In other words, the lesser the GM–WM concentration inside this network, the higher the EI traits. Consistently, the same network showed an opposite (positive) correlation between GM and WM concentration and anxiety scores; the higher the GM–WM concentration, the higher the anxiety. Last but not least, EI was negatively correlated with anxiety. This result is in line with a previous study (Wang *et al.*, 2021) that found a possible indirect influence of EI on the link between GM volume and social anxiety. Interestingly, the areas belonging to the IC5 overlap with those involved in the Default Model Networks (DMN) such as the precuneus, the cingulate cortex, the parahippocampal gyrus and portions of the frontal and temporal lobe (Doucet *et al.*, 2019). This result suggests that higher scores in EI and lower scores in anxiety were associated with less increased GM and WM concentration in the DMN. The link between EI and the DMN has been already reported in resting-state fMRI studies (Takeuchi *et al.*, 2013; Killgore *et al.*, 2017; George *et al.*, 2018; Ling *et al.*, 2019), where greater suppression of the DMN associated to EI has been equated to the more general evidence of greater DMN suppression in superior cognitive performance, also when cognitive performance include emotional elements (Pan *et al.*, 2018; Leonards *et al.*, 2023). But as far as we know, this is the first evidence of a link between EI and the structural properties of the regions belonging to the DMN. We interpreted this association in the light of the emerging model of DMN as implied in many psychological problems (Langerbeck *et al.*, 2023). Accumulating evidence aligns with the association of the DMN with anxiety (Saviola *et al.*, 2020; Baggio *et al.*, 2023), borderline personality (Grecucci *et al.*, 2022; Langerbeck *et al.*, 2023), narcissistic personality (Jornkokgoud *et al.*, 2023), anger-related problems (Sorella *et al.*, 2022; Grecucci *et al.*, 2023a) and rumination (Zhou *et al.*, 2020). In sum, our results indicate that the lesser the GM–WM concentration of the regions belonging to the DMN, the lower the anxiety, and the higher the EI.

Due to the strong overlap between the network of areas activated in social cognition and the DMN (Buckner and Carroll, 2007; Schilbach *et al.*, 2008)—especially in the case of higher-order social cognition tasks (e.g. attributing mental states to others)—the results of the present study are also compatible with EI theories that empathizes the importance of social cognition skills (Takeuchi *et al.*, 2013). In a more comprehensive view, the DMN seems to be implicated, more in general, in semantic functions (including representation of generalities concerning social interactions or self-representations) (Binder *et al.*, 2009) and self-projection functions (Buckner and Carroll, 2007), which are the basis for humans' understanding of one's own and others' mental states.

Interestingly, also the anterior insula and the dorsal anterior cingulate cortex (dACC) were involved in the IC5. This suggests the additional intervention of the salience network (SN) in EI. Previous studies have hypothesized that the SN may coordinate the switching between the DMN (internally oriented attention) and externally oriented attention (Christoff *et al.*, 2016). We reason that the efficacy of such coordination, as well as the flexibility in functions switching, could importantly contribute to individual differences in EI. More related with emotional abilities, Zanella *et al.* (2022) found a modulation of blood oxygenation level dependent (BOLD) temporal variability in the salience network associated with both EI trait and emotion regulation strategies.

Further, a negative correlation between EI and GM volume is not uncommon, especially in the temporal lobe (Tan *et al.*, 2014; Yao *et al.*, 2018; Wang *et al.*, 2021), which is involved in the processing of social and affective information and in the EI measures of thinking disposition (Yao *et al.*, 2018). Indeed, lower GM volume in one region would not necessarily indicate worse affective or cognitive function (Aichelburg *et al.*, 2016; Yao *et al.*, 2018). Nevertheless, our results do not support evidence of increased GM volume in prefrontal regions (i.e. orbitofrontal cortex) as brain mark of EI (Koven *et al.*, 2011; Weber *et al.*, 2013; He *et al.*, 2018). Different analysis as well as different measures of EI or its subscale may explain this discrepancy.

The GM feature of the IC10 was also associated with the trait EI. Although the WM counterpart was not statistically associated, we emphasize that the components resulting from the mCC + jICA analysis consist in a covarying concentration of the two modalities and they are correlated. This means that the ICWM10 could be partially involved in the EI. Further studies are needed to support and extend this partial result. In this context we limit our speculations to the association between the EI and the GM concentration in a brain circuit which resemble the reward one, especially for the caudate (Grahn *et al.*, 2008).

Limitations and conclusions

As a first application of the mCC-jICA approach to the investigation of the neural basis of EI, the present study has some limitations to be pointed out. We focused on the construct of EI in terms of personality trait, but we acknowledge that other leading models conceptualized it in terms of abilities (Webb *et al.*, 2013). Future studies should integrate both perspectives for a whole comprehension of EI in terms of neural basis and theorical frameworks.

Another limitation concerns the sample and the imbalance between female and male participants (28% of female). Indeed, there is evidence that EI may depend by gender ant it is reduced in men (Fischer *et al.*, 2018). However, we controlled for age and gender in all our analyses and we could not find any effect of them. Further studies may want to further inquire these aspects. Finally, even if the mCC + jICA is a multimodal neuroscientific approach and helped us to consider multiple brain structural features, these latter should be also integrated with information related to the brain functionality, especially since the relationship between brain volume and connectivity may be inverse (Yao *et al.*, 2018).

Besides these limits, the present study represents a first valuable investigation to exhaustively reveal the neural correlates of EI. It expands our understanding on the brain networks involved in this complex psychological construct by using a pioneering and holistic neuroscientific technique. Our finding paths the way for further research in better delineating the role of the DMN and partially of the salience network, which may parallel those involved in cognitive abilities.

Supplementary data

Supplementary data is available at *SCAN* online.

Data availability statement

The complete LEMON Data can be accessed via Gesellschaft für wissenschaftliche Datenverarbeitung mbH Göttingen (GWDG) https://www.gwdg.de/.

Author contributions

AG: Conceptualization; Methodology, Investigation; Formal analysis; Visualization; Writing - original draft; writing - review and editing. BM: Investigation; Methodology; Formal analysis; Visualization, Supervision; Writing - original draft; writing - review and editing. IM: Writing - original draft; writing - review and editing.

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