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Neural correlates of metacognition in education: a machine learning approach

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ABSTRACT

Metacognition, the ability to reflect and regulate one's cognitive processes, has been shown to play a role in various aspects of life, particularly in academic settings. While important steps have been made in uncovering the neural basis of metacognition for highly specific domains (such as perceptual and mnemonic decision-making), little is known about how these findings relate to general forms of metacognition relevant in education. In this study, we use a data-driven approach to (i) identify brain regions associated with metacognition in education, and (ii) investigate the issue of domain-generality and to what extent these brain regions overlap with regions involved in metacognition in the context of specific decision-making tasks used in cognitive neuroscience. Individual differences in grey-matter volume in the precuneus and neighbouring brain regions were associated with education-related metacognitive knowledge and regulation. We also found overlaps between task-related mnemonic metacognitive abilities and education-related metacognitive knowledge, for example in in the superior frontal cortex. There were also regions specifically associated with metacognition in education, such as the banks of the superior temporal sulcus. Together, our findings suggest a link between lab-setting, domain-specific metacognitive abilities and real-life metacognition in the context of education.

1. Introduction

Reflecting on one's thoughts and beliefs and regulating them is an ability that is key to everyday life decision-making and is known as metacognition (Dunlosky and Metcalfe, 2008). Metacognitive abilities have been found to play a role in psychiatric symptoms (Rouault et al., 2018b), gambling behaviour (Rogier et al., 2021), political polarisation and confirmation bias (Rollwage et al., 2018), but most of all in learning (Zimmerman, 2001) where the notion originated (Flavell, 1979). Because of their positive role in academic achievement (better metacognitive abilities are associated with higher achievement, Ohtani and Hisasaka, 2018) understanding the underlying mechanisms of metacognitive processes may support the development of interventions. Indeed, there is some evidence that this is possible in specific contexts (Carpenter et al., 2019; Gilbert et al., 2020; Melby-Lervåg and Hulme, 2013; Schwaighofer et al., 2015; Soveri et al., 2017). However, whether such interventions show benefits beyond the lab and/or specific tasks remains unclear. The underlying issue is the domain-generality or specificity of metacognition. For instance, it remains unclear to what extent domain-specific metacognitive processes studied in neuroscientific research reflect, or are constituent of, metacognitive processes taking place in and affecting everyday learning in educational settings (Fleur et al., 2021). Understanding these issues can orientate practice towards the most efficient approaches for training metacognitive abilities (Fleur et al., 2021).

In the past decade, neuroscientific research made progress in understanding the neural mechanisms of metacognition (Katyal and Fleming, 2023). In neuroscientific research, finding neural correlates of metacognition has been operationalized by deriving a metacognitive metric from performance in a decision-making task, and identifying regions of interest that significantly correlate with that metric (e.g., Fleming et al., 2010; Fleming and Dolan, 2012; McCurdy et al., 2013), or tracking brain regions that are activated during such tasks (Morales et al., 2018). In most of those tasks, participants are asked to differentiate between two stimuli and then report their confidence in their decision. In such tasks, participants engage in what are called *metacognitive*

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judgements, in which participants reflect on and make judgements about prior decisions. Using mathematical tools borrowed from signal detection theory (Galvin et al., 2003), the relationship between decision accuracy and confidence rating can be computed, giving a measure of metacognitive abilities (Fleming and Lau, 2014; Maniscalco and Lau, 2012). These measures may reflect either *metacognitive sensitivity* – one's ability to correctly estimate their accuracy in the task –, or *metacognitive efficiency* – the quality of one's metacognitive judgements, independently of task difficulty and performance. Intuitively, individuals present high metacognitive sensitivity when 'how confident they rate their performance' coincides with their actual performance. In other words, they are more likely to report high confidence when they correctly discriminated between the signals, and low confidence when they did so incorrectly. In contrast, sensitivity is poor when confidence rating does not coincide well with performance (Fig. 1).

There is accumulating evidence from both structural and functional MRI research of a role of the lateral and medial anterior prefrontal cortex (aPFC) in metacognitive sensitivity, metacognitive efficiency and during metacognitive judgements in perceptual decision-making tasks (Baird et al., 2013; Fleming et al., 2010; Morales et al., 2018; Rahnev, 2021; Rouault et al., 2018a; Vaccaro and Fleming, 2018). In addition, grey-matter volume in the frontal pole has been associated with metacognitive sensitiviy in this domain (McCurdy et al., 2013) and functional imaging study have found a role of the insula and anterior cingulate cortex (ACC) in both metacognitive sensitivity and efficiency (Baird et al., 2013; Morales et al., 2018). Research on mnemonic metacognition (both sensitivity and efficiency) indicate a role of the precuneus, lateral and medial PFC, and inferior parietal lobule (Baird et al., 2013; McCurdy et al., 2013; Vaccaro and Fleming, 2018). One review article and one meta-analysis have compared the findings of studies investigating specific domains of metacognition to infer domain-generality in the brain (Rouault et al., 2018a; Vaccaro and Fleming, 2018). These two studies highlight a combination of domain-specific and domain-general networks. For instance, Vaccaro and Fleming (2018) included both structural and functional MRI data in their meta-analysis and found evidence for both perceptual and mnemonic metacognition in the posterior medial frontal cortex and in the right insula/inferior frontal gyrus. The dorsolateral PFC (dlPFC) was associated with both domains but not in an overlapping way. The perception domain was associated with the right hemisphere, and the memory domain with the left hemisphere. Specific to mnemonic activations was the parahippocampal gyrus. Note that only a handful of neuroimaging studies have directly investigated the domain-generality of metacognition (Baird et al., 2013; McCurdy et al., 2013; Morales et al., 2018; Rouault and Fleming, 2020). In short, there is emerging but still little evidence available about the neurocognitive basis of metacognition across domains.

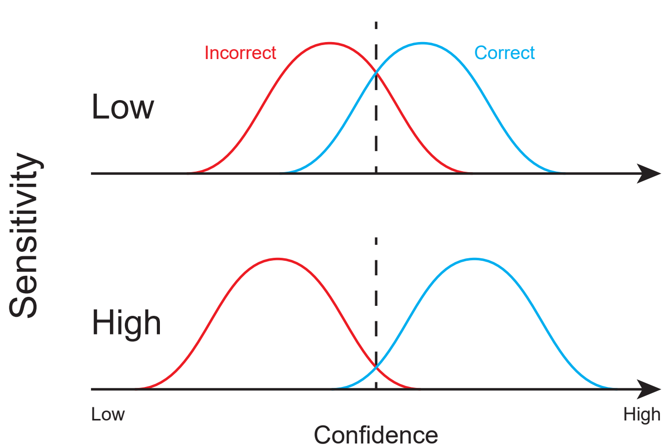

Fig. 1. An intuitive representation of low vs. high metacognitive sensitivity. The red and blue curves represent the distribution of confidence ratings in making the correct choice for incorrect and correct trials, respectively. The smaller the overlap between the two curves, the larger the metacognitive sensitivity.

In educational sciences, mainly two frameworks are used to study metacognition (Dinsmore et al., 2008). The first stems from Flavell's seminal work on metamemory from which the term metacognition stems (Flavell, 1979; Flavell and Wellman, 1977). This framework is epistemologically very close to the framework used in cognitive neuroscience. Two types of metacognition are distinguished. On the one hand, metacognitive knowledge is the acquired knowledge about one's own cognitive processes and the ability to monitor and reflect on them – metacognitive judgements being one specific type of metacognitive knowledge. On the other hand, metacognitive regulation is the ability to use that knowledge to strategically regulate these cognitive processes (Livingston, 2003). These two type of metacognition are often assessed with context-sensitive self-reported questionnaires, such as the Metacognitive Awareness Inventory (MAI; Schraw and Dennison, 1994). The second framework often used in educational sciences is Self-Regulated Learning theory (SRL). SRL does not make an explicit distinction between metacognitive knowledge and metacognitive regulation. Rather, its contribution lies in viewing metacognition as one of several components that enable students to engage strategically with their learning (Pintrich and Garcia, 1994; Zimmerman, 2002). In other words, SRL can be viewed as an extension from Flavellian metacognition incorporating components related to motivation and beliefs.

In previous research we have argued that the definition of metacognitive knowledge presented above is theoretically compatible with metacognitive judgements (Fleur et al., 2021). In both cases, participants make introspective assessments about their abilities with regards to a task, which are often reported as explicit ratings. The task may be an experimental one in which a narrow set of skills and cognitive processes are deployed, such the ones used to study metacognitive judgements. In contrast, it may be a learning task performed in educational settings and involving a wide variety of domains going from decision-making (e.g. problem solving) to memory (e.g. test on learned material) to knowledge about performance expectations, learning strategies and self-efficacy. These two examples highlight an important difference in the scope in which metacognition is studied in cognitive neuroscience and educational neurosciences. Note that the temporal distance between activity and introspective thought is very different in the two examples presented above. While metacognitive judgements in laboratory tasks are performed after each trial, self-report questionnaires measure metacognitive knowledge about activities that may have taken place days or even weeks prior.

Little is known regarding to what extent evidence from neuroscience also holds in educational settings (Fleur et al., 2021). One recent study investigated the potential relationship between metacognitive sensitivity in a mnemonic task, on the one hand, and metacognitive knowledge and regulation on the other hand, which was assessed with the MAI questionnaire (Terneusen et al., 2023). They found that neither metacognitive knowledge or regulation significantly predicted metacognitive sensitivity. However, another study did find a relationship between accuracy in retrospective metacognitive judgements about learning and scores in either or both metacognitive knowledge and regulation, as assessed with the MAI (Jang et al., 2020). This may indicate that the domain overlap between education-related and task-related metacognitive abilities is thin, but not conceptually incompatible. In fact, one could view these different measures of metacognition as part of a spectrum, ranging from local involving few modalities in simple tasks to global in which various cognitive and metacognitive modalities interact at different levels and to different degrees in complex tasks. More generally, it is currently unclear to what extent task-based metacognitive sensitivity and efficiency map onto other measures of metacognitive abilities in learning in the brain (such as the MAI). On the one hand, metacognitive efficiency is viewed as a more robust assessment of metacognition and assumed to be independent of task performance

(Fleming and Lau, 2014; Rahnev, 2025), which makes is the favoured option in most cases. On the other hand, self-report questionnaires like the MAI are context-dependent in the sense that the academic environment (i.e., the course(s), curriculum and study year, as well as general life factor) plays an important role in the degree to which a student is metacognitively engaged in their learning. Research suggests that motivation, for instance, plays an important role in promoting SRL (Linnenbrink and Pintrich, 2002; Pintrich, 1999, 2000). Metacognitive scores from self-report questionnaires may thus be more akin to metacognitive sensitivity. While several studies have investigated neural correlates of metacognitive sensitivity using structural MRI (Allen et al., 2017; Baird et al., 2015; Fleming et al., 2010; Sinanaj et al., 2015; Valk et al., 2016), only McCurdy et al. (2013) have, to our knowledge, done so for metacognitive efficiency. This study being explorative in nature, both sensitivity and efficiency are investigated with regards to the MAI.

Efforts to link task-related metacognitive abilities to more general forms of metacognition are emerging. Lund et al. (2023) investigated metacognitive sensitivity and efficiency across the perceptual, memory and two domain-general knowledge domains, nutrition and global economics. Their results indicate some degree of domain-generality for MS, with some domains correlating significantly and others not, and a greater degree of domain-generality for metacognitive efficiency. Interestingly, neither sensitivity nor efficiency correlated significantly with two general knowledge domains, despite involving similar cognitive processes. This may suggest that prior beliefs related to real-world knowledge may play a strong role in metacognitive abilities.

How to address these outstanding challenges? The aim of this study is twofold. First, we make a first step into the neuroanatomical basis of metacognition in educational settings by investigating the relationship between grey matter volume (GMV) and metacognitive abilities. Second, we investigate the issue of domain-generality and to what extent these brain regions overlap with regions associated with metacognition in the context of decision-making tasks. This can be done thanks to the existence of widely used and validated measurements from each field, that are based on the same theoretical framework.

We focus on structural brain measures because they have been found to have a high test-retest reliability, which makes them best suited for studies focussing on individual differences approaches to neuroscience (Bennett and Miller, 2010; Dubois and Adolphs, 2016; Elliott et al., 2020; Hedges et al., 2022). Furthermore, given the sparse evidence on the relationship between metacognition and brain structure, as see above, this study adopts an exploratory approach. Following recent developments in brain research, and cognitive sciences to a larger extent, we use data-driven, machine-learning methods to detect features (in this case brain regions) that play a role in metacognitive abilities. This approach is well suited for big datasets with many variables, since it reduces the risks of overfitting and can handle non-linear relationships.

A general assumption in neuroscience is that brain structure (at least partly) determines and predicts brain function (Batista-García-Ramó & Fernández-Verdecia, 2018; Segall et al., 2012). However, research shows that this relationship is complex and non-trivial (Batista-García-Ramó & Fernández-Verdecia, 2018; Litwińczuk et al., 2023). For instance, regions that are not directly anatomically connected can still show functional connectivity (Litwińczuk et al., 2023). Nevertheless, there appear to be topological similarities between structural and functional networks and computational models have been able to simulate activity from structural data (Batista-García-Ramó & Fernández-Verdecia, 2018). In metacognition research, structural evidence for a role of the aPFC have been later confirmed in functional studies (Rouault et al., 2018a; Vaccaro and Fleming, 2018), suggesting a structural basis for functional engagement. In fact, review studies have often incorporated both types of data in their analyses. This shows direct mapping of structure onto function is possible to some extend and that structural MRI research can inform future fMRI studies.

Investigating individual differences in GMV also makes it possible to draw parallels with the body of evidence on the role of brain structure in cognitive abilities relevant for education. For instance, greater GMV in the PFC is associated with better executive functions (Yuan and Raz, 2014) and grey matter density in the dlPFC was related to higher academic performance (Wang et al., 2017).

2. Materials and methods

2.1. Participants

187 students (95 females, age range: 17–55; M(SD) = 20.80(3.94)) at the University of Amsterdam took part in the experiment. Participants either identified as male or female and had normal or corrected-to-normal vision. Both left and right-handed participants were included. All signed an informed consent for the experiment and received either a monetary reward (€25) or research credits. They also received a monetary bonus based on their performance in the behavioural tasks (up to €6). The study was approved by the ethical committee of the University of Amsterdam. After applying the exclusion criteria (see section 2.2.3), 160 students were included in the statistical analysis (81 females, age: 17–27; M(SD) = 20.24(1.98)).

2.2. Metacognitive judgement tasks

Two 2-alternatives forced-choice tasks (2AFC) were used to assess metacognitive abilities in two different cognitive domains. The order in which the tasks were performed was randomly assigned for each participant. The first task operationalises metacognition in the visual memory domain (henceforth called memory task; Fig. 2a) and was borrowed from Fleming et al. (2014), itself adapted from McCurdy et al. (2013). At the beginning of each of the four blocks, participants were presented with a list of 50 English words for 1 min that they had to memorise as well as possible. They were informed when there were 10 s left in the memorising phase. In each trial of the block, two words appeared on the left and right of the screen, one belonging to the list (old word) and one that did not (new word). Participants had to select with the left and right arrows of the keyboard which of the words was the old one. They then rated how confident they were in their choice by using the same keyboard arrows to move the cursor on a scale of 1 (low confidence) and 6 (high confidence). In both tasks, participants were encouraged to use the whole scale. The task consisted of four blocks of 50 trials, making up 200 trials in total. The order of the blocks was counterbalanced per participant.

The second task was used to evaluate metacognition in the visual perceptual domain (henceforth called perception task; Fig. 2b) and was borrowed from Rouault et al. (2018b). Contrary to Rouault et al. (2018b) implementation, the task was not staircased (i.e., task difficulty was not adapted to ensure uniform performance across subjects), as it has been shown to influence metacognitive ability estimates (Rahnev and Fleming, 2019). After being presented by a fixation cross for 1000ms, two black boxes were presented, each containing varying pseudo-randomly positioned white dots for 300ms. Participants had to select with the left and right arrows of the keyboard which of the two boxes contained more dots and subsequently rate their confidence in their choice on a scale from 1 to 6, in which 1 stood for 'certainly wrong', and 6 'certainly correct'. The task consisted of 114 trials in total divided into four blocks, as well as an instruction and practice block to help participants familiarise themselves with the task.

The meta-*d'* and M-ratio measures were used to operationalise metacognitive sensitivity and efficiency, respectively. These measures were computed with the help of the HMeta-d toolbox for MATLAB (Fleming, 2017) using individual trial-by-trial accuracy and confidence ratings. Thus, two measures of metacognitive abilities were computed from two tasks each, resulting in four measures which we will henceforth refer to as memory meta-*d'*, memory M-ratio, perception meta-*d'* and perception M-ratio.

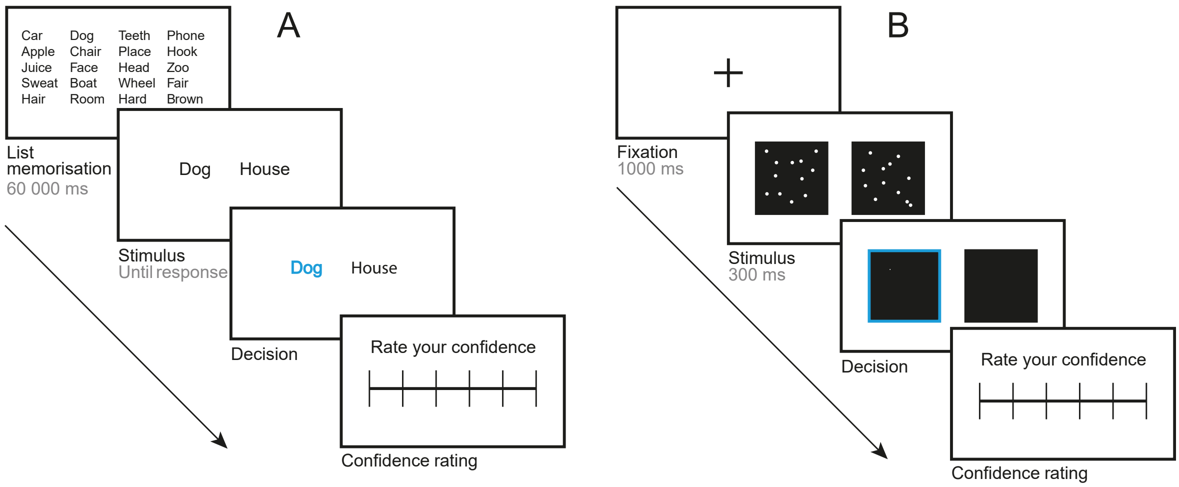

Fig. 2. Overview of the two behavioural tasks used to assess metacognition. A: Memory task. At the start of every block, a list of words is presented that the participant has to memorise. In each trial, two words are presented and the subject has to select the one that was present in the list. They then rate their confidence in their decision on a scale. B: Perception task. Two boxes with randomly generated dots are shown on the screen. The participant then selects which on the two boxes they think contains more dots. They then rate their confidence in their decision on a scale.

2.3. Metacognitive awareness inventory

Due to their good validity and ease of use to study big cohorts (Harrison and Vallin, 2018), self-report questionnaires have been among the most popular method in educational settings to assess metacognitive abilities. In this study, a shortened, 19-item version of MAI (MAI; Harrison and Vallin, 2018) was used. These items were identified using confirmatory factor analysis (CFA) and multidimensional random coefficient multinomial logit (MRCML) item-response modelling. This version showed better validity compared to the original 52-item version from Schraw and Dennison (1994) and other proposed versions. This version of the MAI is composed of two scales: metacognitive knowledge (e.g., “I am aware of what strategies I use when I study”) and metacognitive regulation (e.g., “I change strategies when I fail to understand”), operationalising one’s own knowledge about learning materials and behaviour, as well as regulation of it, respectively. The participants were told to think about their current courses when rating the statements on a five-point Likert scale (1 = Not at all typical of me, 2 = Not very typical of me, 3 = Somewhat typical of me, 4 = Fairly typical of me, and 5 = Very typical of me). A measure if metacognitive knowledge and metacognitive regulation is then computed by taking the mean rating of the statements belonging to each scale, respectively. In the remaining of this paper, we will refer to these two measures as MAI-knowledge and MAI-regulation.

2.4. MRI data acquisition and processing

The structural imaging data were acquired on a Philips 3.0 T scanner (Philips Achieva DS, 32-channel head coil). The scan consisted of two high-resolution T1-weighted anatomical scans (voxel: 0.70 × 0.81 x 0.70 mm3; FOV: 256 × 256 × 180; matrix size: 368 × 318 x 257 slices; TR: 11 ms, TE: 5.2 ms, flip angle: 8°; parallel acquisition technique: SENSE). The image was generated by averaging the two scans.

The MRI data were automatically pre-processed using the automatic pre-processing pipeline (fMRIPrep version 1.5.4) provided by the Spinoza Centre for Neuroimaging (Esteban et al., 2019, 2020; RRID: SCR_01621) and based on Nipype 1.3.1 (Gorgolewski et al., 2011; RRID: SCR_002502). This included artifact removal, cortical surface generation, skull-striping, cross-modal registration and standard space alignment. They were corrected for intensity non-uniformity with N4BiasFieldCorrection (Tustison et al., 2010), and skull-striped with a Nipype implementation of the antsBrainExtraction.sh, which are both part of the Advanced Normalization Tools package (ANTs 2.2.0; Avants et al., 2011). Next, the brain tissue was segmented. Each participant’s structural image was segmented into white matter, grey matter and cerebrospinal fluid using FAST (FSL 5.0.9, fsl.fmrib.ox.ac.uk/; Zhang et al., 2001). Brain surfaces were reconstructed using recon-all (FreeSurfer 6.0.1.; Dale et al., 1999).

2.5. Grey matter volume extraction

GMV region parcellations were extracted with Freesurfer (surfer.nmr.mgh.harvard.edu) using the Desikan-Killiany atlas (Desikan et al., 2006) for cortical regions and FreeSurfer’s default atlas for subcortical regions (aseg). To correct for brain size variation across subjects (O`Brien et al., 2011), the GMV of each brain region was scaled using the SupraTentorialVolNotVent parameter, which is the estimation of the intracranial grey and white volumes, excluding cerebellum, brain stem, ventricles, CSF and choroid plexus). This parameter was used for scaling instead of the total intracranial volume, which was inconsistent across subjects for the following reasons: i) the size of the ventricles influences white and grey matter volume; ii) limitations of the data acquisition material that did not always allow to scan the whole brain. As a result, the cerebellum often had to be cut off during scanning, since it was viewed as least likely to be related to metacognition. Since the cerebellum could not be fully captured for all participants, ROIs of the DK atlas overlapping with this region were excluded from the analysis.

2.6. Feature extraction

A Random Forest (RF) regression with feature permutation importance was performed to identify brain regions related to metacognition, using scikit-learn (version 0.24.2; Pedregosa et al., 2011). This algorithm was adapted from de Groot et al. (2024). One advantage of RF over other regression techniques is that it can capture non-linear relationships and is viewed to be a robust model (Breiman, 2001). The set of features on which the RF regression was trained consisted of the 83 brain regions derived from the Desikan-Killiany atlas (Desikan et al., 2006), as well as the control variables age and sex. All features were scaled between 0 and 1 to allow for comparison. The RF regression uses an ensemble of independently constructed decision trees. Each decision tree is trained on a different, randomly selected, bootstrapped sample of the data and set of features. The prediction – a measure of importance per feature – produced by all the trees is then averaged into one prediction, which makes it possible to rank features based on their importance for predicting an outcome.

A leave-one-out cross-validation outer loop was applied (LOOCV; Molinaro et al., 2005). In particular, the data was split in each loop such that the data related to one participant was used to evaluate the model and the data of the remaining participants was used to train it, resulting in a total of 160 models (1 per participant). This method was preferred over more widely used lower-fold cross-validation (usually with 5 of 10 folds, as opposed to N folds in the case of LOOCV) due to the relatively small size of our dataset compared to the tens of thousands of samples used for typical machine learning algorithms. LOOCV allows an increase in the number of data points used to fit the model, reducing the risk of overfitting, as well as the bias of the model. The number of decision trees was set to 1000 and the other hyperparameters were kept at default to keep a balance between reliability and robustness on the one hand, and computational cost on the other.

To improve the reliability of the measure of importance produced by the RF regression, feature importance was assessed using permutation importance (Altmann et al., 2010; Breiman, 2001). The metric works by computing for each feature the difference between the actual performance of the model (expressed as mean square error, or MSE) with that of a version of the model in which the values for the evaluated feature have been randomly permuted. In other words, the more important the feature, the higher the MSE of the model when permutated, resulting in a higher permutation importance. Note that permutation importance is not a linear metric. For instance, if features X and Y have permutation importance of 0.01 and 0.02, respectively, this does not suggest that Y is twice as important as X. To mitigate the risk that random values incorrectly indicate high permutation importance due to chance, permutation importance was averaged over five permutations for each feature. As a result of the LOOCV and permutation importance each feature gets assigned 160 measures of permutation importance.

To evaluate which features play a meaningful role in predicting metacognition, a baseline feature ('RANDOM') was included in the set of features. The values of the RANDOM feature consisted of randomly generated values between 0 and 1. This way, this feature can act as a baseline to be compared against the permutation importance of other features. Features whose permutation importance is significantly higher than that of the RANDOM feature (Students' one-tailed t-tests, $p < 0.05$ with Bonferroni correction) were thus considered to be meaningfully associated with metacognitive abilities. Conversely, the features that were not significantly higher we considered as junk and were excluded from the final set of features. The following analyses have been performed and their results can be found in the supplementary materials: (*i*) an alternative Random Forest regression with the RANDOM feature drawn from a normal distribution (Fig. S3), and (*ii*) linear regressions drawn from the set of meaningful features identified in the main Random Forest Regression (Fig. S5).

2.7. Exclusion criteria

Participants were excluded if they (i) performed below or near chance level (<55 %) in either of the two tasks, (ii) failed to rate their confidence on more than 3 different points on the confidence scale. In addition, individual trials were excluded if (iii) no answer was registered, and if response time (RT) was higher than 10s or deviated by more than 3 standard deviations (SD) from their mean RT, (iv) because of a bad fit of the meta-d' to the confidence rating data resulting in negative values, (v) due to incomplete or corrupted data, (vi) if their age deviated by more than 2 SD from the mean age of the participants, or (vii) if their computed M-ratio was indicative of a bad fit (i.e., negative or deviating by more than 3 SD from the mean). As a result, 27 participants and 2.1 % of the trials were excluded from the analysis.

3. Results

3.1. Behavioural results

Pearson correlation tests of the different measures of metacognition indicates an association between perception and memory meta-*d'*, as well as some level of association between memory meta-*d'* and MAI-knowledge (Fig. 3). The strong correlation between the knowledge and regulation components of the MAI is surprising given Harrison and Vallin's (2018) analysis of the inventory. See appendix for extended results.

3.2. Neuroimaging results

In the memory domain, 11 features were associated meta-*d'*, and 13 for M-ratio (Fig. 4). For the perception domain, the number of predictive features was 11 for both meta-*d'* and M-ratio. Lastly, 15 features were associated with MAI-knowledge and 18 with MAI-regulation. For the sake of conciseness, only the top 5 features of each domain are illustrated in Fig. 4. See Fig. S2 and Table S3 for the full overview.

3.2.1. Overlap

One feature was found to overlap between MAI-knowledge and both memory meta-*d'* and M-ratio, namely the left superior frontal region. Similarly, only the right caudate overlapped with perception meta-*d'* and MAI-knowledge. Regarding MAI-regulation, there was an overlap with memory M-ratio in the left isthmus cingulate and right caudal middle frontal regions; with memory meta-*d'* in the right caudal middle frontal region; with perception M-ratio in the left rostral anterior cingulate; and with perception meta-*d'* in the left superior temporal region (Fig. 5).

4. Discussion

While progress has been made into the neural basis of metacognition, research has so far been confined to specific tasks in laboratory settings. The question remains open as to what the current body of evidence means for more general use of metacognition, such as in educational settings. The aim of this study was to (i) identify brain regions associated with metacognitive abilities related to education and (ii) investigate the issue of domain-generality and to what extent these brain regions overlap with regions involved in metacognition in the context of simple cognitive tasks, building a bridge between educational and cognitive neuroscience. Here we will first review our results on simple task, emphasizing they are largely consistent with previous findings and thus provide a solid foundation for the follow up analyses. Next, we discuss the neuroimaging results associated to (i) the MAI components, then more specifically at (ii) domain-general regions overlapping metacognitive knowledge in learning (MAI-knowledge) and task-related mnemonic and perceptual metacognitive sensitivity and efficiency (meta-d' and M-ratio), and *iii*) domain-generality for education-related metacognitive knowledge and task-related metacognitive sensitivity and efficiency. Finally, we discuss limitations of the current studies and future directions.

In terms of the simple tasks, our results are in line with earlier findings (see Fig. 4 and S3). In the memory domain many regions previously reported were found in our study. This is the case for the frontal and medial frontal regions as well as lateral (medial) frontal regions such as the caudal middle frontal, pars opercularis and pars orbitalis. Interestingly, we found no association between individual differences in brain volumes in the precuneus and mnemonic metacognitive abilities, though we did find such association for adjacent regions, such as the paracentral and supramarginal regions memory M-ratio. In the perception domain, the parahippocampal region was among the most important features associated with meta-d'. This region has been identified in a meta-analysis (Vaccaro and Fleming, 2018), though notably in relation

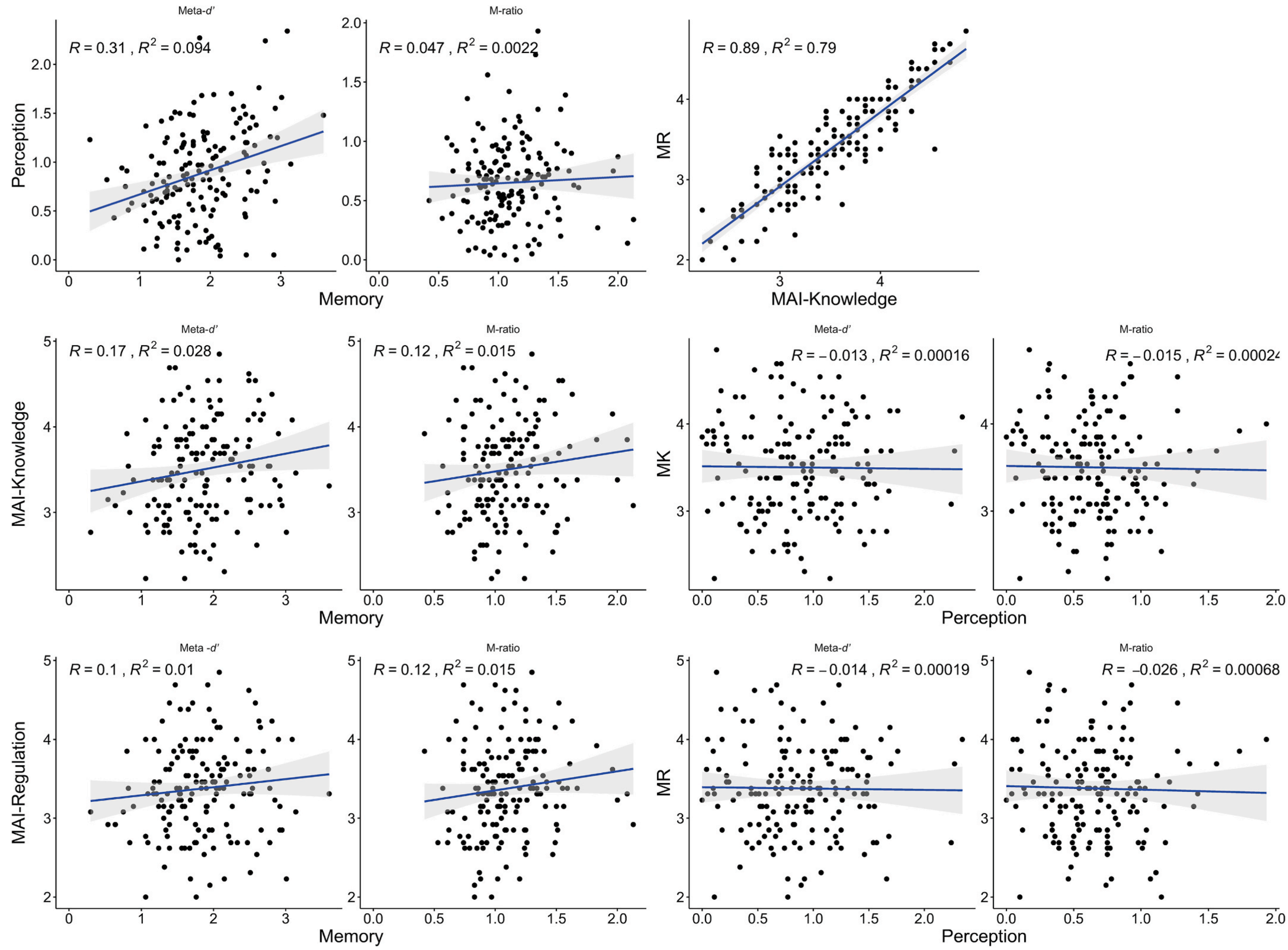

Fig. 3. All correlations between measures of metacognition with one another.

to the memory domain, not the perception domain. Individual differences in the rostral middle frontal, rostral anterior cingulate and superior frontal regions (i.e., lateral aPFC, ACC and medial aPFC, respectively) were all associated with perception M-ratio. All these regions have been previously linked with perceptual metacognition and monitoring in functional neuroimaging studies (Baird et al., 2013; Fleming et al., 2012; Morales et al., 2018; see Fleur et al., 2021). Together, these results indicate that the Random Forest algorithm produced results consistent with those that have been previously reported based on linear models.

Individual differences in the precuneus and neighbouring regions, such as the posterior cingulate and superior parietal regions were associated with MAI-knowledge (see Fig. 4). Furthermore, Individual differences in brain volumes were most strongly associated with MAI-regulation in the rostral anterior cingulate. Notably, individual differences in volumes in the precuneus was also associated with MAI-regulation. In previous studies (both functional and structural MRI), the precuneus has been specifically linked with mnemonic metacognitive abilities (Baird et al., 2013; McCurdy et al., 2013) and memory at large. In other words, neural characteristics related to metacognition for specific tasks involving memorisation are also associated with metacognition for education. Indeed, memory is a central component of learning and is also captured in the MAI (e.g. the following item: "I know what kind of information is most important to learn"). Finally, individual differences in the left banks of the superior temporal sulcus (labelled bankssts) were found to be specifically associated with the MAI components, as opposed to any of the measures for metacognitive judgements in tasks. This region has been found to play an important role in theory of mind (Hein and Knight, 2008), but did not overlap with metacognition in a meta-analysis (Vaccaro and Fleming, 2018). This may indicate that metacognition in educational settings involves a wider range of high level, reflective processes that are not typically engaged in metacognitive activities during lab tasks.

Next, we examined to what extent mnemonic and perceptual metacognitive abilities are related metacognitive knowledge in learning to identify domain-general characteristics. Specifically, we looked at overlapping regions. The superior frontal region is the only one for which individual differences in grey-matter volume were associated with both MAI-knowedge and task-related metacognitive abilities in the memory domain (i.e., meta-*d'* and M-ratio). This region can be related to the posterior medial frontal cortex, which has been found to play a domain-general role (Vaccaro and Fleming, 2018). In the perceptual domain, the caudate nucleus was the only region for which individual differences were associated with both MAI-knowledge and meta-*d'*. There was no overlap between MAI-knowledge and perception M-ratio. While the superior cortex is a large region that overlaps with regions typically linked to metacognition (Fleur et al., 2021), the caudate nucleus has, to the best of our knowledge, only been reported in fMRI research (Baird et al., 2013) to play a role in perceptual metacognitive sensitivity. It has however been found to play a role in processing confidence prediction error and is anatomically richly connected to the prefrontal cortex (see Cortese, 2022). Error prediction is viewed as an

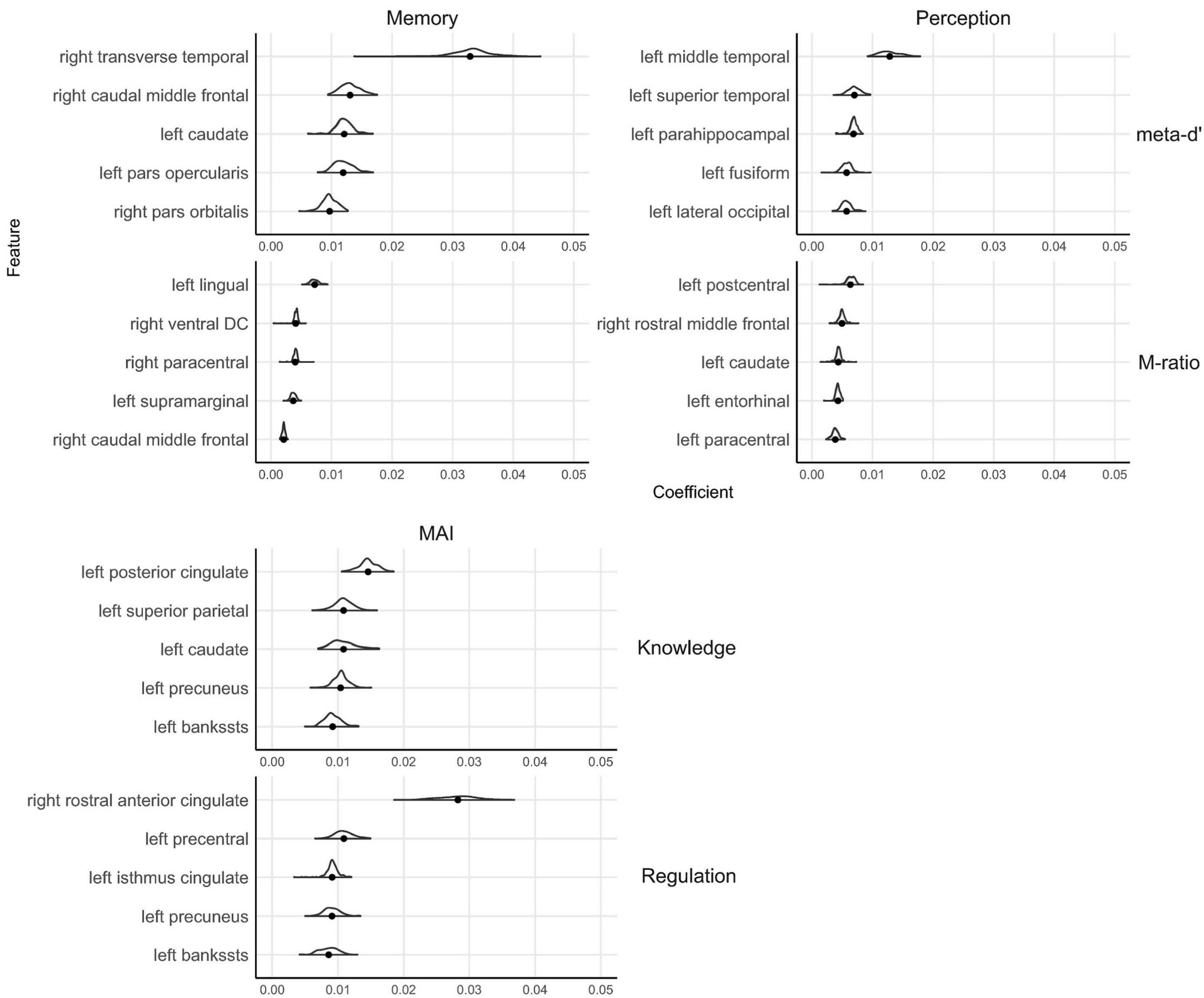

Fig. 4. Mean and violin distribution of the top 5 features of each domain with permutation importance significantly higher ($p < 0.05$) than that of the randomized feature (RANDOM) in Bonferroni corrected, one-tailed t-tests.

implicit, or online form of metacognitive process which operates automatically and largely unconsciously, as opposed to metacognitive judgements in which participants engage in introspective thoughts (Fleming and Dolan, 2012; Fleur et al., 2021; Frith, 2012) These findings support the idea that metacognition knowledge for education is associated with a set of regions that are also engaged in specific domains of metacognition. Conversely, this suggests that metacognition related to lab tasks do in fact reflect to some extent real-life metacognition. Given the central role of memory in academic curriculums, we speculate that the type of metacognition in a recognition memory task is comparable, or at least relevant, to metacognitive activities related to learning a foreign language or memorising the content of a textbook for an exam.

Following analyses on MAI-knowledge, we turned our investigation to MAI-regulation. Our results suggest that individual differences in the caudal middle frontal region is associated with MAI-regulation, memory meta-*d'* and memory M-ratio. This region has been widely reported both in the metacognition literature and in the adjacent executive function literature, which studies regulatory cognitive behaviours (see Fleur et al., 2021). Furthermore, our we found that individual differences in volumes in the rostral anterior cingulate cortex were associated with both education-related metacognitive regulation and, in line with previous studies, task-related perceptual metacognitive efficiency. Moreover, the rostral anterior cingulate cortex was also associated with education-related metacognitive knowledge. In short, regions involved in domain-specific metacognitive judgements (a form of metacognitive knowledge) were found to be also associated with domain-general regulatory processes. It is important to note, however, that we found a significant correlation between MAI-knowledge and MAI-regulation (Fig. 3), which is surprising given how this version of the MAI was constructed. Moreover, more than half of the regions associated with these two components overlap (Fig. S2). It is therefore unclear to what extent the brain regions identified are associated with either of both MAI components.

4.1. Limitations and future directions

The findings presented in this paper are a first step into bringing metacognition research beyond the lab and obtain a more global understanding of metacognition in a way that could benefit other fields of research, education in particular.

First of all, the strong correlation between the knowledge and regulation components of the MAI and the large set of shared brain

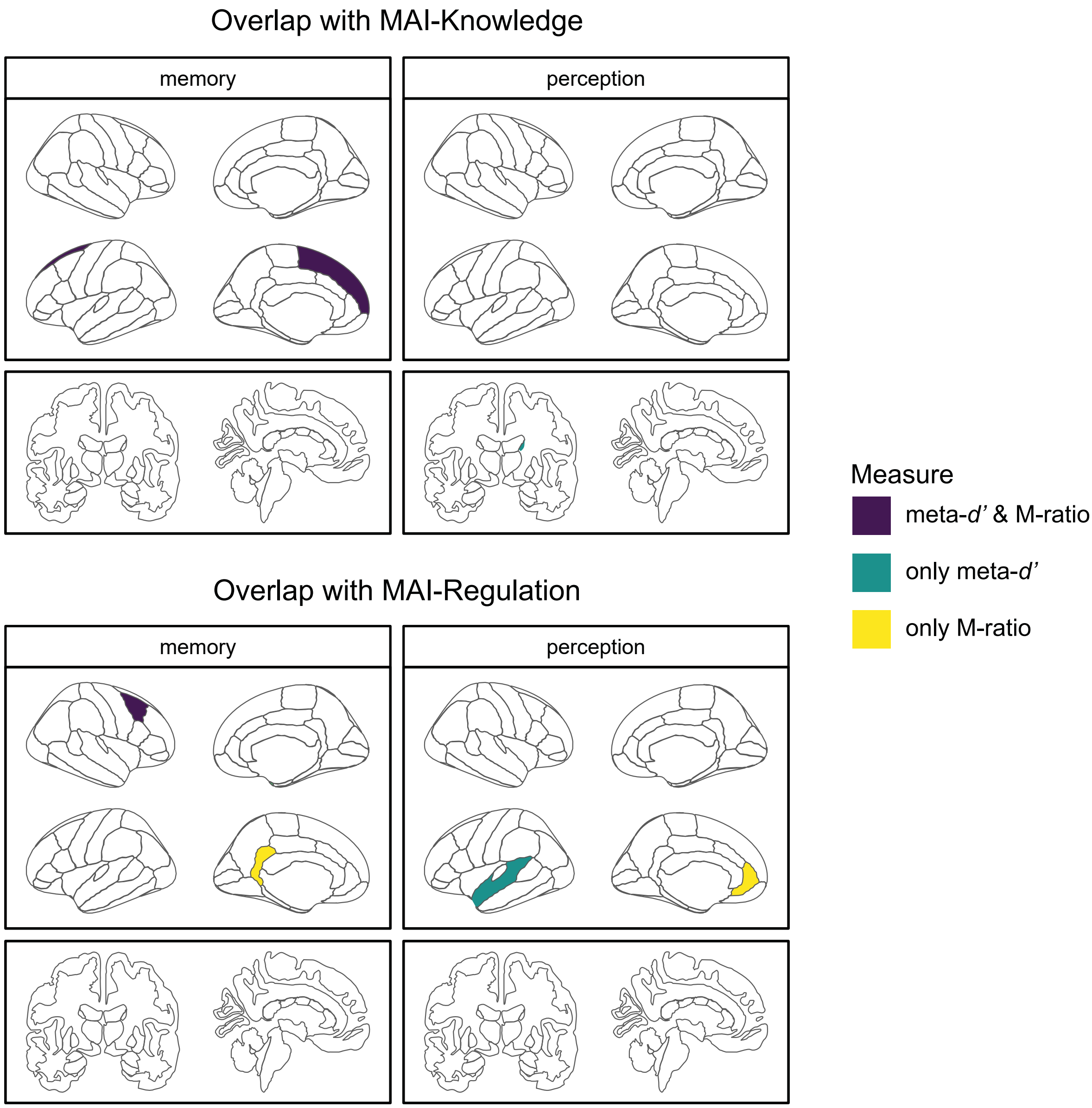

Fig. 5. Overlap between the features associated with the MAI-knowledge and MAI-regulation scales and memory/perception meta-d'/M-ratio.

regions is remarkable. In theory, and based on the work of Harrison and Vallin (2018), these components should be clearly distinct, which was not the case in this study. However, there appears to be some unique variance between MAI-knowledge and MAI-regulation since our results show different overlaps with either the perceptual or mnemonic domain. Moreover, Vaccaro and Fleming (2018) have noted other instances in which behavioural measures were correlated but were not necessarily associated with the same neural traces. In this light, our results should be interpreted with care and future confirmatory research is necessary.

Second, there is an important difference between our task-based and self-reported measures of metacognition when it comes to the underlying activity on which participants make introspective judgements. While decisions in the tasks are made in a matter of seconds, a learning activity may typically last minutes to hours. Similarly, the time allocated for reporting on introspective thoughts (confidence rating on the one hand and likert-scale on the other) was set for the tasks but not for the questionnaires. As a result, both decision and metacognitive judgements in the tasks may have been more influenced by pre-conscious processes, a “hunch" (Fleming and Lau, 2014), and MAI scores by self-beliefs.

Third, a limitation of Random Forest regressions is that they do not allow to report on the nature of the relationship between brain structure and behavioural measure. For instance, it is unclear whether increased or decreased grey matter volume is associated with greater metacognitive ability. We have performed linear regressions using the sets of features identified in the Random Forest regression as predictors (Fig. S5). While the coefficients obtained from the regression may give some indication on the direction of the relationship between brain volume and metacognition, they cannot as such be used to explain the role of these regions in metacognition since Random Forest regressions capture non-linear relationships. Future research is therefore needed to unpack the non-linear relationships identified in this study. Future research should also aim at integrating structural and functional imaging data to provide a more comprehensive understanding of the neural basis of metacognition.

Fourth, we relied on the DK atlas for brain parcellation. Future studies using other atlases with more parcels may reveal that an apparent overlap consisted of adjacent, non-overlapping regions associated with different metacognitive domains. Importantly, however, a more fine-grained atlas would require a proportionally bigger sample.

Fifth, future study should investigate the role of metacognition in education in interaction with socio-cognitive and affective factors. While we specifically selected the MAI as a measure of metacognition in education due to its good theoretical overlap with metacognition is cognitive neuroscience, many models of metacognition in academic learning insist on the role of social cognition, instructional setting and affect on the extent to which a learner is metacognitively active (Pintrich, 2000; Zimmerman, 1995). Note that knowledge and regulation of these aspects can also be viewed as forms of metacognition.

Finally, future studies should develop new paradigms that allow to reflect more closely the kind metacognitive processes that are at play in education settings. Ideally, such paradigms would be designed in a way that allows for direct comparison with metacognitive assessments from 2AFC tasks such as the ones used in this study. Doing so may lead to a better understanding of how domain-specific metacognitive processes may combine and interplay in real life settings. Furthermore, it is likely that metacognitive processes that are related to different domains, such as mnemonic and perceptual decision-making, may play a differential role in learning depending on the learning task itself. It is indeed uncontroversial that mathematics and language learning involve both common and distinct skills. In turn, this knowledge may enable researchers to develop intervention that target domains of metacognition that would have been identified as central and/or trainable in a way that will benefit learners. Given evidence for the neuroplasticity of brain structure (Perdue et al., 2022), future research could investigate in longitudinal studies how the identified brain regions relate to the development of metacognitive abilities. It would also be interesting to evaluate the effects of metacognitive training protocols on brain structure.

4.2. Conclusion

In sum, our study was able to identify brain regions associated with domain-general education-related metacognition. They consist of both previously reported regions such as the precuneus and the anterior cingulate cortex, but also of others, such as the superior temporal sulcus which is related theory of mind, another form of high-level, reflective process. Furthermore, we provide evidence for a link between domain-specific, task-related metacognition and real-life, education-related metacognition by identifying overlapping regions. For instance, we found that individual differences in the left superior frontal cortex were associated with both mnemonic and education-related metacognitive knowledge. Furthermore, our results suggest an overlap between perceptual and education-related metacognitive knowledge in the left caudate nucleus. These findings are an encouraging starting point for future interdisciplinary research. In the future, this may lead to a better understanding of metacognition in educational settings and its role in learning behaviour and academic success in interaction with socio-cognitive and affective aspects.

CRediT authorship contribution statement

Damien S. Fleur: Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Esra C.S. de Groot:** Software, Project administration, Investigation, Data curation. **Bert Bredeweg:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Wouter van den Bos:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuropsychologia.2025.109265.

Data availability

The anonymised data and analysis scripts used for this study are made available on OSF (https://osf.io/ndk8y/?view_only=fc0ba0c40de64c9fa13e29dd153ae3bb)

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