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Partially overlapping neural correlates of metacognitive monitoring and metacognitive control

Abbreviated title: Metacognitive monitoring and control

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Abstract

Metacognition describes the process of monitoring one's own mental states, often for the purpose of cognitive control. Previous research has investigated how metacognitive signals are generated (metacognitive monitoring), for example when people (both f/m) judge their confidence in their decisions and memories. Research has also investigated how metacognitive signals are used to influence behavior (metacognitive control), for example setting a reminder (i.e. *cognitive offloading*) for something you are not confident you will remember. However, the mapping between metacognitive monitoring and metacognitive control needs further study on a neural level. We used fMRI to investigate a delayed-intentions task with a reminder element, allowing human participants to use their metacognitive insight to engage metacognitive control. Using multivariate pattern analysis, we found that we could separately decode both monitoring and control, and, to a lesser extent, cross-classify between them. Therefore, brain patterns associated with monitoring and control are partially, but not fully, overlapping.

Significance Statement

Models of metacognition commonly distinguish between monitoring (how metacognition is formed) and control (how metacognition is used for behavioural regulation). Research into these facets of metacognition has often happened in isolation. Here, we provide a study which directly investigates the mapping between metacognitive monitoring and metacognitive control at a neural level. We applied multivariate pattern analysis to fMRI data from a novel task in which participants separately rated their confidence (metacognitive monitoring) and how much they would like to use a reminder (metacognitive control). We find support for the notion that the two aspects of metacognition overlap partially but not

50 fully. We argue that future research should focus on how different metacognitive signals are
51 selected for control.

Our brains possess a remarkable ability to monitor performance and to then use *metacognition* to control future behavior. For example, if you have low confidence that you will remember a delayed intention (*metacognitive monitoring*; *MetaM*) like regular medication intake, you might set a reminder on your phone (*metacognitive control*; *MetaC*). This distinction between monitoring and control is found in the seminal metamemory framework by Nelson and Narens (1990; see also Flavell, 1976; Kluwe, 1982; Brown, 1987; Efklides, 2008; Shea et al., 2014; Yeung et al., 2004; Fleming & Daw, 2017; Fletcher & Carruthers, 2012; Fleur, Bredeweg, & van den Bos, 2021), which proposes that cognition functions at two distinct levels: the object and the meta level (Figure 1A). Information at the object level about decisions, memories, attention, action and so forth is re-represented at the meta level via a process of *MetaM*. Meanwhile, information at the meta level controls processing at the object level (*MetaC*). Shimamura's (2000) dynamic filtering theory extends the framework by Nelson & Narens (1990), ascribing the role of the object level to posterior cortical regions and the role of the meta level to prefrontal cortex (PFC). The information flow between these regions forms the basis of *MetaM* and *MetaC*.

We are only slowly beginning to understand the neural mapping between *MetaM* and *MetaC*. This mapping or link describes the relationship that exists between *MetaM* and *MetaC* on a functional level – are these labels describing the identical process or two different computations with different inputs? This question is important because one rationale for studying *MetaM* is that it can provide insight into *MetaC* (e.g. Boldt & Yeung, 2015; Wokke et al., 2020; Masset et al., 2020; Gherman & Philiastides, 2018; Miyamoto et al., 2018; Odegaard et al., 2018; Bang & Fleming, 2018; Ye et al., 2018; Shekhar & Rahnev, 2018). This would be strengthened if the mapping between the two were better understood. Furthermore, dissociations have been found between *MetaM* and *MetaC*. For example, in some circumstances, young children (Redshaw et al., 2018), OCD patients (Vaghi et al.,

2017) older adults (Dunlosky & Connor, 1997), and individuals with Autism Spectrum Conditions (Grainger et al., 2016) have a diminished mapping between MetaM and MetaC, which could lead to suboptimal behavioral regulation. However, the potential neural substrates for this variability are unknown.

One of the reasons why the MetaM-MetaC mapping has received little attention is that the two aspects of metacognition are usually studied in isolation (though see Koriat et al., 2006, 2014; Mei et al., 2020; Son & Schwartz, 2009; Schulz, Fleming & Dayan, 2021; Qiu et al., 2018). Studies on MetaM commonly explore the variables that affect how confident people feel and the associated neural correlates. For example, neuroimaging studies have identified a widespread network of involved regions, including the rostrolateral prefrontal cortex (rlPFC; Yokoyama et al., 2010; Fleming, Huijgen, & Dolan, 2012; Allen et al., 2017) and also the precuneus specifically for metamemory studies (e.g. McCurdy et al., 2013; Baird, Smallwood, Gorgolewski, & Margulies, 2013; Ye et al., 2018). Moreover, machine-learning techniques have been used to “decode” brain patterns associated with low versus high confidence, using both fMRI (Hebart et al., 2014; Cortese et al., 2016; Morales, Lau & Fleming, 2018) and EEG (Boldt & Yeung, 2015). Research on MetaC, on the other hand, has focused on situations in which metacognitive experiences are utilized for learning, communication, or speed-accuracy tradeoff, to name a few (e.g. Metcalfe & Finn, 2008; Guggenmos et al., 2016; Lak et al., 2020; Shea et al., 2014; Bahrami et al., 2010; Desender et al., 2019; Frömer, Nassar, Bruckner, Stürmer, Sommer, & Yeung, 2021).

Most of what we know about the link between monitoring and control comes from the field of cognitive control and error monitoring. Electrophysiological correlates have been found that signal not only when an error has been committed but are also sensitive to correct-trial performance fluctuations (Allain et al., 2004; Yeung, Botvinick, & Cohen, 2004). Such monitoring of errors often results in lower response speed immediately after a mistake, a

robust and often-replicated phenomenon termed post-error slowing (Rabbitt, 1966; Danielmeier & Ullsperger, 2011; Notebaert et al., 2009). In addition to errors, conflict signals appear to be monitored by the posterior medial frontal cortex (pmFC) including the dorsal anterior cingulate cortex (dACC). The lateral prefrontal cortex (lpFC) is thought to receive this input and implement cognitive control (Ridderinkhof, Ullsperger, Crone, Nieuwenhuis, 2004). It should be noted that participants are often not aware of such errors or response conflicts and that these studies are not directly measuring metacognitive signals. Nevertheless, evidence from this domain suggests that similar brain regions support metacognitive monitoring and control. Qiu and colleagues (2018) conducted four elegant fMRI experiments, using a decision-redecision paradigm: Participants were presented twice in a row with each stimulus and rated both their response and confidence for each presentation. They reasoned that participants would engage metacognitive monitoring for their initial response and use metacognitive control to revise and improve decisions in the redcision phase. Their analyses revealed an involvement of dACC in the first response and lpFC in the second. However, because the order of the decision-redecision phases was always the same, it is impossible to conclude whether the redcision phase really triggered more MetaC or whether the signal observed in lpFC was instead a ‘late’ monitoring one. Another open question is whether MetaM and MetaC rely on similar representations.

In order to address these questions, it is necessary to study both aspects of metacognition in a single paradigm, which we did using a cognitive offloading task. Cognitive offloading is the use of physical action to reduce cognitive demand, e.g. setting external reminders rather than relying on internal memory. Previous research has demonstrated a MetaM-MetaC link whereby individuals are more likely to set reminders (MetaC) when they have low confidence in their memory abilities over and above the influence of their actual memory performance (MetaM; Risko & Gilbert, 2016; Hu et al.,

2019; Dunn & Risko, 2016). This finding is a robust pattern that can even be observed when reminder setting is not explicitly instructed (Boldt & Gilbert, 2019) or when confidence was measured in an unrelated perceptual task (Gilbert, 2015). Here, we use a decoding approach to examine this link at a neural level.

Participants performed a delayed intention task where in separate blocks they engaged in MetaM (how confident am I that I will remember?) or MetaC (how much would I like a reminder?). This allowed us to answer two questions: 1) Do similar brain patterns characterize MetaM and MetaC? If so, 2) Can the neural patterns that characterize specific acts of MetaC be exhaustively characterized in terms of their associated processes of MetaM? We answered these questions by examining cross-classification between MetaM and MetaC: the extent to which a classifier trained on one judgement can decode the other. Insofar as this is possible, this implies a shared neural code for MetaM and MetaC. But if cross-classification is weaker than decoding MetaM and MetaC individually, this implies that their neural bases do not overlap fully.

Materials and Methods

Participants

We trained 29 participants in a behavioral task during a first session. After reviewing their training data, 22 participants returned to the lab for a second MRI session 1 to 21 days later, excluding 7 participants (2 unsuited for MRI due to safety regulations, 2 had extreme staircase values, 3 were unavailable for a second session). Another participant was excluded after scanning due to excessive movement in the scanner. This resulted in a final sample of 21 participants, out of which 15 were female and 6 were male. While we determined our sample size based on practical constraints and on available resources, the final sample size of $N=21$ is nevertheless in accordance with previous MRI studies using similar methods

(Morales et al., 2018, Qiu et al., 2018; Hebart et al., 2014). Participants were 20.3 years on average (18 – 26 years and paid £36 for their participation in both sessions (about 90 and 150 minutes). All participants were right-handed, had intact color vision, no uncorrected visual impairments and had not been diagnosed with any psychiatric or neurological disorders. All testing was approved by the local ethics committee and participants gave informed consent prior to taking part in the study.

Experimental Design

In order to investigate the extent to which neural patterns associated with MetaM and MetaC are similar or distinct we had to study both aspects of metacognition within a single paradigm. Participants underwent short miniblocks of ongoing shape discrimination trials. For this ongoing task, participants had to quickly and accurately decide whether an array of colored shapes grouped around a fixation dot looked on average more like a circle or a square (De Gardelle & Summerfield, 2011) by pressing one of two buttons. The response categories were equally likely. During some of these miniblocks, participants also had to maintain a delayed intention to press a different button if the stimulus appeared in a target color (Figure 1B). Participants were allowed to use reminders (cognitive offloading) to support their prospective memory in approximately half of the miniblocks, which meant that the central fixation dot of the stimulus took on the target color for the duration of the miniblock. Instead of having to rely on their memory, participants could then simply wait for the color of the shapes to match the color of the fixation dot, making the fulfilment of the delayed intention much easier. There were 12 colors, placed equidistant in RGB space. Within each miniblock, colors were drawn without replacement. There was only one target color per miniblock, presented at the beginning of the miniblock, and its occurrence during the ongoing-task trials always terminated the miniblock.

The task comprised three within-subject experimental conditions (20% Baseline, 40% MetaM, and 40% MetaC; see Table 1) each structured into miniblocks. A miniblock comprised presentation of a target color (except for in the Baseline condition which had no prospective memory element), a single metacognitive rating or cursor placement, followed by 3-7 ongoing-task trials. The number of trials per miniblock was drawn from an exponential distribution with a mean of $\mu = 1.1$, in other words shorter miniblocks were more frequent than longer miniblocks. Each of the eight blocks consisted of 94 shape trials spread unevenly across 40 miniblocks (see Figure 1C). The critical difference between our two key conditions was the metacognitive rating given about the target color before each miniblock. In the MetaC condition, participants reported how much they would want to set a reminder to help them remember this target color. The higher the rating given by the participant, the greater the likelihood of receiving a reminder, which occurred on approximately 50% of miniblocks. More specifically, ratings larger than the moving median of the past 20 MetaC ratings were assigned a reminder, whereas ratings below this cutoff had to be solved using only unaided memory. In the MetaM condition, participants reported their prospective confidence in remembering the target color. However, this had no influence on the likelihood of receiving a reminder, which occurred on a randomly selected 50% of miniblocks. In other words, the two conditions also differed in the relationship between participants' ratings and the provision of reminders. In the MetaM condition, participants' ratings had no influence on whether or not they received a reminder. In the MetaC condition, on the other hand, which miniblock contained a reminder was largely determined by participant's ratings. Therefore, in the MetaM condition participants engaged in metacognitive monitoring but did not exercise metacognitive control. In the MetaC condition they exercised control to make a decision which is known to be guided by metacognition (Boldt & Gilbert, 2019; Gilbert, 2015). However, they were not explicitly asked to make a direct metacognitive judgment.

In the Baseline condition, there was no target color and thus no prospective-memory component (and no need for a reminder). The rating participants were asked to give was thus an ‘empty’ one, that is a scale without labels but with a cursor was presented on screen together with two little markers indicating where the cursor should be placed on the scale. Participants then had to move the cursor to the indicated position. In all three conditions, participants were instructed to move the cursor at least once to submit a rating.

Each block was comprised of only two out of the three conditions, the Baseline condition together with either the MetaM or the MetaC condition and alternated between the two. Within each block, conditions were predictable, that is they always followed the order of one Baseline miniblock followed by four other miniblocks. We determined the optimal order of conditions using simulations, allowing us to maximize the efficiency of our design. The main analysis window was the initial 7 seconds of the task (presentation of target color and rating). At the time of these prospective ratings, participants were still unaware whether or not they would receive a reminder, keeping our key contrast free of confounds, which would have been unavoidable had we chosen a retrospective confidence judgement as is more commonly used in the field. To increase the number of instances this analysis window was shown we therefore included partial miniblocks, that is half of the time (20 miniblocks per run), the miniblock ended immediately after the rating without the need to perform any shape classification trials or search for the target.

The study comprised two sessions. The purpose of the first session was assessment of MRI safety, completion of a pre-study questionnaire on how much participants liked the 12 colors used in the task, and training in the behavioral task (presented in MATLAB using Psychtoolbox3; Kleiner, Brainard, Pelli, Ingling, Murray, & Broussard, 2007). Participants first completed eight practice blocks, each introducing them to a new aspect of the paradigm. They then completed four experimental runs that were identical to the task they would have

to complete whilst in the scanner, each lasting ~9 minutes. During the second session, participants first underwent two practice blocks outside of the scanner (each lasting ~5 minutes) to remind them of the task before they completed eight runs in the scanner, with a 6-minute T1 scan between the fourth and fifth run. One participant only completed six blocks due to feeling unwell inside the scanner. Due to the unbalanced design, we decided to exclude this participant from all multivariate analyses.

At the end of the second session, participants were furthermore asked to fill in a post-experiment questionnaire, asking them to rate the liking of all colors again, together with how difficult they found them and several additional questions to determine whether they perceived the MetaM and MetaC conditions as similar, how much control they felt during these conditions, how they used the reminders depending on whether or not they asked for them, and how they approached each rating. The orientation of the rating scales was flipped halfway through the experiment to avoid confounding visuomotor processes with low versus high ratings. The order of scale orientations, response keys for the shape task, and the order of the conditions were counterbalanced across participants.

MRI Data Collection and Preprocessing

We used a 1.5T Siemens Avanto scanner with a 32-channel head coil and MRI-safe button boxes. We acquired both T1-weighted structural images, as well as T2*-weighted echoplanar images (EPI; 64 x 64; 3.2x3.2x3.2 mm voxels) with blood oxygen level-dependent (BOLD) contrast. We used a multiband acquisition sequence with acceleration factor = 3, TE = 54.8 ms, flip angle = 75°, to record 39 interleaved, axial slices (3.2mm thick, oriented approximately to the anterior commissure - posterior commissure plane). This allowed us to cover most of the brain with an effective repetition time of 1.3s per volume. Encoding phase direction was anterior to posterior. Functional scans were acquired in eight

runs, each comprising 410 volumes (~9 min). The first five volumes in each session were discarded to allow for T1 equilibration effects. Between the fourth and fifth functional scans, an approximately 6 min T1-weighted MPRAGE structural scan was collected.

All preprocessing was done using SPM12 (<https://www.fil.ion.ucl.ac.uk/spm/software/spm12/>). The T1-weighted images were skull stripped and their origin was set to the anterior commissure. We then realigned the EPI volumes and normalized them into 3 mm cubic voxels with fourth-degree B-spline interpolation using normalization parameters derived from segmentation of the co-registered structural scan, then smoothed with an isotropic 8 mm full-width half-maximum Gaussian kernel.

Statistical Analysis

Analyses of behavioral data were conducted using R version 3.6.0 (“Planting of a Tree”) with the additional packages *plyr*, *plotrix*, *Hmisc*, *R.matlab*, *viridis*, *effsize*, *raincloudplots*, *ggplot2*, *grid*, *gridExtra*, and *Rmisc*. Statistical tests were conducted two-sided if not stated otherwise. For *t*-tests we reported effect sizes as Cohen’s *d*, and for ANOVAs as partial eta square η^2_p . For the fMRI analyses, the volumes acquired during the eight sessions were treated as separate time series. For each time series, the variance in the BOLD signal was decomposed with a set of regressors in a general linear model. Three regressors were generated to code for the target color presentation and the rating as a 7s boxcar, separately for miniblock and rating conditions (Baseline in MetaM blocks, low MetaM rating, high MetaM rating in MetaM blocks and Baseline in MetaC blocks, low MetaC rating, high MetaC rating in MetaC blocks). Six additional regressors were generated that represented effects of no interest, specifically, stimulus presentation as a stick function, separately for targets and non-targets, the ongoing task spanning from the onset of the first to

the last shape stimulus of the miniblock, separately for whether there was a prospective-memory requirement (Baseline vs. MetaM and MetaC) and the time when the computer revealed to the participant whether they were allowed to use a reminder as a stick function, separately for Reminder and Own Memory miniblocks. All regressors were convolved with a canonical hemodynamic response function. The regressors outlined above, along with six regressors representing residual movement-related artefacts and the mean over scans comprised the full model for each session. The data and model were high-pass filtered at a cutoff of 1/128 Hz. Parameter estimates for each regressor were calculated from the least mean squares fit of the model to the data. Effects of interest were assessed in a random-effect analysis by first forming subject-specific contrasts subtracting the Baseline from the other two conditions. The resulting contrast images were entered into a repeated-measures ANOVA using nonsphericity correction (Friston, Glaser, Henson, Kiebel, Phillips, & Ashburner, 2002), representing a condition agnostic selection contrast to identify a network of regions active in the rating task. Results are reported applying a height threshold of $p < 0.001$ uncorrected in conjunction with an extent threshold determined by SPM12 to achieve $p < 0.05$ familywise error correction for multiple comparisons across the whole brain volume. Region of interest (ROI) analyses were conducted by extracting subject-specific contrast estimates from the resulting ROIs with the toolbox MarsBaR (Brett, Anton, Valabregue, Poline, 2002), then entering the resulting data into an ANOVA in R using the same correction procedure described above.

The logic behind the key analysis of our study was the following: Replicating and extending previous findings (Hebart et al., 2014; Cortese et al, 2016; Morales et al., 2018) we first trained separate classifiers to detect A) whether participants were in a high or low confidence state (MetaM), and B) whether they had high or low desire for a reminder (MetaC). These classifiers could then also be combined in a cross-classification analysis, that

302 is whether a classifier trained on MetaM ratings can also predict MetaC ratings (and vice
303 versa). Insofar as this cross-classification is possible, this suggests shared brain
304 representations for both aspects of metacognition. Going one step further, we then compared
305 within-category classification to cross-classification accuracy to distinguish between two
306 possible patterns of results: If MetaM and MetaC are based on the exact same
307 representational code, there should be no difference in classification accuracy. If, on the other
308 hand, MetaM and MetaC share partially overlapping patterns, we should find significantly
309 higher classification accuracy for within- than across-category classification, but
310 significantly-different-from-zero accuracy for cross-classification.

311 For the multivariate-pattern analyses, we used The Decoding Toolbox (TDT; Hebart,
312 Görgen, & Haynes, 2015), based on the beta images resulting from the previously described
313 general linear models (except that the models were re-fit to unsmoothed, unnormalized data
314 and the MetaM and MetaC boxcar regressors were split into two regressors each using a
315 median split on the respective metacognitive rating). When we ran our four separate decoding
316 analyses, two drew the training and testing data from the same condition (low vs. high ratings
317 for the MetaM and MetaC conditions respectively; defined by block-, condition- and subject-
318 wise median splits), whereas the other two cross-classified (train on low vs. high MetaM
319 ratings and test on high vs. low MetaC ratings and vice versa; note that the rating scale had to
320 be flipped for MetaC as low confidence implies high desire for a reminder). For each of these
321 analyses, a linear support vector machine (SVM) was trained to discriminate between low
322 versus high ratings given the patterns of BOLD activity across voxels. Given the alternating
323 block design and the fact that the orientation of the scale was flipped halfway through the
324 study, we had two low and two high rating images available for each training or testing fold,
325 resulting in a 2-fold procedure (see Figure 1D).

We used a whole-brain searchlight approach (Kriegeskorte, Goebel, & Bandettini, 2006), meaning that for each voxel a separate SVM was built, fitted to the beta values within a sphere with a radius of 3 voxels (9.6 mm). This resulted in three-dimension decoding accuracy maps in native space for each participant and analyses. Decoding accuracy is calculated relative to chance level (subtracted by 50%, so a 5% accuracy corresponds to 55%). These maps were then normalized into Montreal Neurological Institute (MNI) space (using the same normalization parameters as the univariate analyses) and smoothed using a Gaussian kernel (full-width half-maximum, 4mm). Please note that this kernel was half of the one used for the univariate analyses. This was done to avoid excessive smoothing, given that the searchlight analysis already imposes spatial smoothing on the data. The resulting images were entered into a one-sample *t*-test using SPM12. This allowed assessment of voxels showing consistently higher decoding accuracy in a random-effect analysis. We note that the suitability of second-level *t*-tests has been challenged for information-like measures such as classification accuracy, where classifier performance can meaningfully be above, but not below, chance levels (Allefeld, Görden & Haynes, 2016; Hirose, 2020). However, this characteristic does not apply to our two key hypothesis-testing analyses. For the cross-classification between MetaM and MetaC, high MetaM could either predict higher or lower MetaC. For the comparison between within- and cross-classification, accuracy for one classification could be higher or lower than the other. Therefore, in both cases our statistical tests are valid because they are performed on data that could meaningfully take values both above and below zero.

Along with the main MVPA analyses described above, we conducted an additional analysis. Here, we used a similar approach to the univariate ROI analysis described above by defining a condition agnostic contrast (the mean of all four decoding analyses), extracting ROIs with significantly above-chance decoding accuracy and then entering the resulting

classification accuracies into a repeated-measures ANOVA with factors ROI, Training condition (MetaM/MetaC), and Classification type (within-condition/cross-classification).

Results

Behavioral Results

Our sample included 22 participants, one of which was excluded due to excessive motion in the MRI scanner, see Methods for more details. Participants performed the tasks with a high level of accuracy (mean shape-discrimination accuracy = 93.4%, SEM = 0.84%; non-significant shape bias, $t(20) = 1.2$, $p = 0.25$, $d = 0.26$; mean target-detection rate = 88.1%, SEM = 3.37%; NB chance target-detection accuracy would be 8.3%; false alarm rate = 0.8%). With our design, we decided against using a direct manipulation of difficulty (such as spacing some colors closer to each other in color space) as this would have made it difficult to interpret any effect of confidence due to its inherent confound with a difficulty manipulation. Instead, we relied upon natural fluctuations in confidence, caused for example by individual preferences for colors or fatigue. Figure 2A shows that average, unaided memory performance varied across colors with some colors (e.g. the 4th color, a shade of green) being associated with lower accuracy when participants had to remember this target color unaided by a reminder. Moreover, this figure shows that not all participants had the same inherent color-difficulty profile and that instead some participants perceived particular colors as more difficult than others. Performance in the Baseline condition was high. Here, an indicator of compliance with instructions is participants' placement of the cursor between two thin lines marked on the scale (Figure 2B). Participants reported that those lines were difficult to see in the scanning session. Nevertheless, their cursor locations peaked around the marked location and landed within the marked positions on approximately half the trials, $\delta = 47.6\%$.

We next established that the reminders aided participants in their fulfilment of the delayed intentions by comparing target-detection error rates for miniblocks in which participants had to use their own memory (fixation dot stayed white) to miniblocks in which they were allowed to use a reminder (fixation dot took on target color), shown in Figure 2C. In both conditions, error rates were reduced when reminders could be used ($F(1,20) = 20.5$, $p < 0.001$, $\eta^2_p = 0.51$; $t_s > 3.4$, $p_s < 0.01$, $d_s > 0.37$ when tested separately for the MetaM and MetaC conditions). Error rates did not differ significantly between conditions, $F < 1$, nor was there an interaction between the two factors, $F < 1$.

When asked explicitly after the experiment how similar they perceived the two conditions, participants rated the conditions as similar but not identical ($M = 0.68$ on a scale from 0 = ‘totally different’ to 1 = ‘exactly the same’; min = 0.28; max = 0.98). In fact, we found that participants’ perception of the two conditions differed in how much control participants felt they had over the reminders. On a scale ranging from 0 = no control to 1 = full control, participants rated the MetaM condition with a mean of $M = 0.32$ (min = 0.00; max = 0.88) and the MetaC condition with a mean of $M = 0.80$ (min = 0.06; max = 0.98). This difference was significant, $t(20) = 6.4$; $p < 0.001$, $d = 1.94$. This shows that participants were able to grasp the key difference that distinguished the two conditions.

We furthermore aimed to rule out that any condition differences found in the pattern classification analyses could be caused by behavioral differences in how the different ratings were approached. Firstly, Figure 3A shows that the average ratings participants gave for each individual color were almost indistinguishable whether they were giving a metacognitive-monitoring or metacognitive-control rating. In fact, if we correlated the average ratings for each color for each individual participant, there was an average relationship of $r = 0.76$ with 19 out of 21 participants showing a significant, positive relationship between the MetaM and the MetaC rating for different colors. Relatedly, participants’ rating and rating RT

distributions for the two types of ratings were closely matched (Figures 3B and 3C). It is important to note that participants did not receive any instructions to use these scales in the same way (except for being asked to use the entire range of the scale in both cases).

Futhermore, neither of the metacognitive rating conditions showed a systematic relationship between confidence and accuracy: For retrospective confidence judgements, it is commonly found that these correlate, that is participants express lower confidence on errors than on correct trials (confidence resolution or type-II sensitivity). In the MetaC condition on the other hand, participants' ratings triggered reminders, so we would expect to see the opposite pattern: Trials for which they expressed a high need for a reminder should naturally be the ones on which they were allowed to offload and error rates should therefore be lower. However, we found no significant difference between correct- and error-trial ratings in any of the four conditions (MetaC reminder, $t(14) = 0.2, p = 0.88, d = 0.04$; MetaC own memory, $t(19) = 0.1, p = 0.95, d = 0.02$; MetaM reminder, $t(17) = 1.0, p = 0.34, d = 0.30$; MetaM own memory, $t(20) = 1.1, p = 0.28, d = 0.23$; participants with missing data excluded from the respective analysis). We furthermore correlated the dichotomous accuracy vector with our continuous confidence measure for all four data cells, separately for each participant. The distributions of these correlations are shown in the right panels of Figure 3D. None were significantly different from zero, $ts < 1.0, ps > 0.32$. Taken together, both the prospective nature of the ratings in the present task (i.e. participants might have felt they needed to invest more into trials in which they felt less confident or wanted a reminder more) and our unique offloading design could potentially have led to a reduced confidence resolution, but this was the case for both rating conditions.

Univariate fMRI Results

We first performed univariate analyses to identify brain regions activated by the requirement to encode new intentions and make metacognitive judgements about them. We therefore averaged across the two metacognition conditions (MetaM and MetaC) and compared them to the Baseline condition, allowing us to find regions of interest (ROIs) activated by our task. After family-wise error correcting for multiple comparisons, this contrast revealed seven regions showing increased BOLD signal in the metacognitive conditions (see Table 2 and Figures 4A and 4B).

Within the seven ROIs, activity was then compared between the metacognition conditions. More specifically, activity was extracted in two separate contrasts (MetaM > Baseline and MetaC > Baseline) and then compared. Note that this comparison is orthogonal to the initial selection contrast and therefore unbiased (Kriegeskorte, Simmons, Bellgowan, & Baker, 2009). BOLD signal was higher for the MetaC than the MetaM condition in all seven ROIs (Figure 4C) and this main effect was significant when examined in a ROI (7) x Condition (2: MetaC/MetaM) repeated-measures ANOVA, $F(1,20) = 8.1, p = 0.01, \eta_p^2 = 0.29$. There was furthermore a reliable main effect of ROI, $F(7,140) = 7.8, p < 0.001, \eta_p^2 = 0.28$, as well as a significant interaction of the two factors, $F(7,140) = 3.4, p < 0.01, \eta_p^2 = 0.14$, reflecting that the absolute signal change and also the difference in signal change was larger in some ROIs compared to others. Taken together, these results show that regions which respond to the conditions requiring delayed intentions and metacognitive judgments showed higher activity when participants rated how much they would like a reminder (MetaC) compared to how confident they were (MetaM).

We repeated the univariate analyses for deactivations, revealing six “task-negative” regions showing decreased signal in the conditions requiring delayed intentions and metacognitive judgments compared with baseline (Figure 5 and Table 3). These regions included the cingulate and paracingulate cortices, supplementary motor area, supramarginal

gyrus, middle and inferior temporal gyri, occipital gyri, and anterior cingulate gyrus. Within these task-negative ROIs, there was more deactivation when participants rated how confident they were (MetaM) compared to how much they would like a reminder (MetaC), however, BOLD signal did not differ significantly between the MetaC and the MetaM condition, $F(1,20) = 1.3$, $p = 0.26$, $\eta_p^2 = 0.06$. There was a reliable main effect of ROI, $F(5,100) = 18.2$, $p < 0.001$, $\eta_p^2 = 0.48$. The interaction was not significant, $F < 1$.

Multivariate fMRI Results

The multivariate analyses allowed us to address our two key questions: 1) Do the brain patterns of different metacognitive experiences also distinguish different acts of control? and 2) Can the neural patterns that characterize specific acts of metacognitive control be exhaustively characterized in terms of their associated metacognitive experiences? In a first analysis, we attempted to decode confidence (MetaM). Figures 6A and 6B show the resulting decoding accuracy maps corrected for chance level and multiple comparisons, resulting in nine clusters that contained meaningful information when predicting whether the brain was currently in a low or high confidence state including the anterior cingulate gyrus, parietal occipital sulcus, central sulcus, superior parietal lobule, superior occipital gyrus, cuneus, precuneus, supplementary motor area, occipital fusiform gyrus, calcarine cortex; superior corona radiata, and precentral gyrus (Table 4).

We then repeated the equivalent analysis for the MetaC condition, again successfully decoding whether participants gave a low or high rating (i.e. desire for a reminder) from five clusters including the occipital pole, lateral occipital cortex, superior parietal lobule, superior frontal gyrus (medial segment), middle temporal gyrus (see Table 4). Together these analyses show that the neuroimaging data contains meaningful patterns that distinguish both different

metacognitive experiences (low vs. high confidence) and different acts of metacognitive control (low vs. high desire for a reminder).

Having established the existence of meaningful patterns across the brain that distinguish different levels both of MetaM and MetaC, we could then ask whether it was possible to cross-classify the two aspects of metacognition. More specifically, we trained classifiers to distinguish low from high confidence beta images (MetaM) and tested them to predict high versus low MetaC ratings. Note that an inverse relationship is expected between MetaM and MetaC ratings, i.e. low confidence predicts high desire for reminder and vice versa. Therefore one of the scales was inverted in order to perform this analysis. Above-chance classification accuracy can be interpreted as overlapping patterns encoding both MetaM and MetaC. The same analysis was then applied to the opposite direction (train on MetaC, test on MetaM). Importantly, we found overlapping patterns that encode these different types of metacognitive ratings. However, only for the latter analysis direction (train on MetaC, test on MetaM) did we find above-chance classification accuracy after correcting for multiple comparisons. The surviving cluster was located in the left superior and middle frontal gyri. These findings show that brain patterns associated with different metacognitive experiences (low vs. high confidence) also distinguish different acts of metacognitive control (low vs. high desire for a reminder).

To address our second key question, we compared classification accuracy resulting from the two different types of classification analyses described above: within-category (test on MetaM and train on MetaM; test on MetaC and train on MetaC) versus across-category classification (i.e. cross-classification: test on MetaM and train on MetaC; test on MetaC and train on MetaM). We first performed a condition-blind analysis by averaging across all four decoding analyses. This identified ROIs that contain information in one or more of the analyses in an unbiased manner, yielding significant effects in the occipital pole, middle

occipital gyrus, parietal cortex (superior parietal lobule, precuneus), superior frontal gyrus, middle frontal gyrus; precentral gyrus (see Table 5 and Figures 6C and 6D). Within the resulting ROIs, classification accuracies in the four analyses could then be compared (see Figure 6E) to address the question whether decoding accuracy differed significantly between the within-condition classification and the cross-classification analyses. Taking an analogous approach to our univariate analysis, these comparisons were unbiased because they were orthogonal to the analysis used to define the ROIs. We entered the classification accuracies from these regions into a repeated-measures ANOVA with factors ROI, Training condition (MetaM/MetaC) and Classification type (within-condition/between-condition cross-classification). There was a significant main effect of Classification type, $F(1,19) = 6.2, p = 0.02, \eta_p^2 = 0.25$, with higher classification accuracy for within-condition classifications than between-condition cross-classifications. This finding can be interpreted as partially overlapping neural representations between MetaM and MetaC as opposed to perfect overlap between the patterns associated with the two aspects of metacognition. Moreover, there was no effect of the conditions on which the classifier was trained or which ROI was analyzed, $F_s < 1$. We found a significant interaction between ROI and category (within vs. between classification), $F(6,114) = 2.4, p = 0.03, \eta_p^2 = 0.11$, reflecting that the difference between within-condition and across-condition decoding analyses was larger in some ROIs compared to others. No other interactions were significant, $F_s < 1$. In sum, while our results demonstrate overlapping patterns between metacognitive monitoring and control, they also suggest that patterns of metacognitive control cannot exhaustively be characterized by associated patterns of metacognitive monitoring when participants report their confidence.

Discussion

Metacognitive monitoring is only valuable insofar as it can subsequently influence control. And metacognitive control can only occur if there are metacognitive representations to begin with, which can then be utilized to adjust future behaviour. The two processes must therefore be intimately related, yet the mapping between them requires further study, especially on a neural level. Here we report three main findings: 1) we can separately decode metacognitive monitoring and metacognitive control; 2) brain patterns of different levels of metacognition monitoring (low vs. high confidence) also distinguish different acts of metacognitive control (low vs. high desire for a reminder); and 3) this overlap in patterns while significant is only partial. These findings suggest that patterns of brain activity corresponding to specific acts of metacognitive control are partially, but not fully, characterized by associated acts of metacognitive monitoring.

Our cross classification analysis revealed involvement of the left superior and middle frontal gyri, which form part of the lateral prefrontal cortex (laPFC) in both metacognitive monitoring and control. The role of the laPFC in metacognition has already been highlighted by previous studies, suggesting a role in domain-general metacognition (Morales et al., 2018; see also Vaccaro & Fleming, 2018), in the readout of sensory information as an input for confidence signals (Shekhar & Rahnev, 2018), and more broadly in a mediating role of more rostral parts of laPFC in metacognitive accuracy (Fleming, Weil, Nagy, Dolan, & Rees, 2010; Rounis, Maniscalco, Rothwell, Passingham, & Lau, 2010). Crucially, the laPFC has also been implied in metacognitive control (Qiu et al, 2018; for reviews see Seow, Rouault, Gillan, & Fleming, 2021; Shimamura, 2000; Fleming & Dolan, 2014) matching its more general proposed involvement in cognitive control (MacDonald, Cohen, Stenger, & Carter, 2000; Ridderinkhof et al., 2004). Our study therefore extends this growing body of research that implies an involvement of the lateral prefrontal cortex in metacognition and cognitive control.

Seeing as MetaC could not be characterized exhaustively in terms of the MetaM judgments we investigated, this raises the obvious question of which other signals might contribute to MetaC. We consider two main possibilities. The first possibility is that non-metacognitive signals also play a role in influencing MetaC. A wide variety of signals may be relevant here, such as motivation, the costs and rewards associated with different levels of performance, serial dependencies, fatigue, states of interoceptive and bodily awareness reflecting endogenous signals like arousal (Allen et al., 2016; Hauser et al., 2017; Rouault, McWilliams, Allen, & Fleming, 2018) and so on. This influence of non-metacognitive signals on metacognitive control was already acknowledged in the seminal paper by Nelson and Narens (1990) introducing their metamemory framework. The influence of a wide variety of signals on control is also central to an influential model from the cognitive control literature, the Expected Value of Control model (EVC; Shenhav, Botvinick, & Cohen, 2013). This model emphasizes the flexibility with which different control signals are selected, based on the costs and benefits associated with these signals. The model proposes that the dorsal anterior cingulate cortex integrates both costs and benefits to form the expected value of control. Seeing as MetaC may involve the integration of multiple relevant signals, including the products of MetaM and additional non-metacognitive signals as well, this could potentially explain the greater univariate signal we observed for the MetaC than the MetaM condition. This suggests the incorporation of additional processes into the MetaC judgement beyond those involved in MetaM. We also note that the factor of within- versus cross-classification interacted significantly with region, even though there was no main effect of region. This suggests that the overlap between MetaM and MetaC is greater in some regions than others.

A second possible contribution to the MetaC condition is the integration of additional metacognitive signals, beyond the confidence judgement required by the MetaM condition. In

573 our task, for instance, participants' desire for reminder might have been influenced not only
574 by confidence in their prospective memory but also confidence in their perceptual
575 judgements. Consistent with this, behavioral evidence suggests that confidence judgements
576 are influenced by a variety of domain-general and domain-specific signals (Gilbert, 2015;
577 Kantner, Solinger, Grybinas, Dobbins, 2018; Rouault et al., 2018). Confidence can be
578 regarded as an explicit representation of uncertainty, and uncertainty exists at multiple levels
579 throughout the brain (as noted by the Bayesian brain hypothesis; Knill & Pouget, 2004).
580 Therefore, the metacognitive signals measured in the MetaM condition probably form only a
581 subset of the metacognitive signals which may have contributed to MetaC judgements.

582 Our paradigm involved measurement of only a single MetaC judgment, which may
583 have been influenced by multiple MetaM signals. In reality, there are multiple types of both
584 MetaM and MetaC. Take for example the situation of a foreign language student studying for
585 a test at her desk during the early evening hours. The student reads a word on a flashcard and
586 we can assume she has access to two relevant metacognitive signals: On the one hand there is
587 the certainty with which the word is perceived in the waning light, the other is the certainty
588 with which the word is recognized from memory. The former confidence should guide her
589 decision whether or not to switch on her desk lamp. The latter confidence should guide her
590 decision whether or not to place the flashcard on the pile marked as 'restudy'. Similarly, the
591 same confidence signal could lead to opposite consequences depending on the situation as
592 shown by Carlebach & Yeung (2021). The authors report that low confidence leads to advice-
593 seeking when the quality of the advice is known and high. However, when the quality of the
594 advice is unknown, people tend to seek advice especially when they have high confidence to
595 test the accuracy of the advisor. How does the brain then 'harvest' these various confidence
596 signals and route them to the appropriate act(s) of metacognitive control? How does it
597 flexibly switch to a different set of signals when required to do so? How are metacognitive

signals weighted by past rewards, and how do such weightings shift when our goals change? Questions such as these could potentially be addressed by adapting the present paradigm to a situation involving two or more forms of metacognitive monitoring and control.

The key finding of our study was the cross-classification between MetaM and MetaC. At a whole-brain corrected threshold, this analysis produced a significant effect in only one direction (train on MetaC and test on MetaM). It is not clear whether this reflects an asymmetry in cross-classification, or simply a thresholding artefact. This could be an interesting question to investigate in future work. Our finding of successful cross classification is in line with the notion that metacognition should be regarded as a cornerstone of cognitive control. Twenty years ago, this point was made prominently by Fernandez-Duque, Baird, & Posner (2000), who drew parallels between metacognitive and executive control functions. Similarly, Yeung & Summerfield (2012, 2014) have suggested that error monitoring, as it is commonly studied in the cognitive-control literature, constitutes an inverse, binary measure of graded confidence. It is therefore not surprising that decision confidence is tracked by a well-established electrophysiological marker of error monitoring, the error positivity (Pe; Boldt & Yeung, 2015). Other empirical examples of links between metacognition and cognitive control are the findings that metacognitive efficiency correlates with cognitive control ability (Drescher, Van Den Bussche, & Desender, 2018) and that confidence modulates the speed accuracy tradeoff on a trial-by-trial basis with participants prioritizing accuracy over response speed after a previous low-confidence decision (Desender et al., 2019). The latter effect is reminiscent of post-error slowing (Rabbitt, 1966; Danielmeier & Ullsperger, 2011; Jentsch & Dudschig, 2009), one of the most extensively studied effects of the cognitive control literature.

Our findings bear some interesting parallels to another recent decoding study: Mei and colleagues (2020) reported the results from two behavioral experiments, each focused on

a different type of prospective decision (belief of successfully classifying a visual stimulus vs. deciding whether or not to attend to the stimulus during the upcoming trial). The authors found that it was possible to use the data from one experiment (awareness ratings, confidence ratings and accuracy in previous trials) to predict the prospective decision from the respective other experiment and vice versa. This cross-classification analysis therefore highlights similarities of metacognitive monitoring (in this case: beliefs of successfully classifying the upcoming stimulus) and metacognitive control (in this case: decision to attend), showing that both aspects of metacognition appear in the context of the same behavioral precursors.

Despite the theoretical distinction between two binary facets of metacognition and the two different labels assigned to the conditions, the conceptual distinction between the two is not as straightforward as it may seem. For example, our MetaM condition might still be considered to involve an act of metacognitive control in the sense that participants need to use their metacognitive knowledge to control the act of placing the cursor on the scale to indicate low versus high confidence. We suggest that the key distinction between the conditions is that metacognitive monitoring involves relatively direct read-out of metacognitive (e.g. confidence) signals, whereas metacognitive control involves the use of the signals to inform more complex behaviors rather than report the metacognitive experience itself. However, seeing as metacognitive reports are, at least to some degree, inferential in nature (Koriat, 1993), metacognitive monitoring and control might be seen as extreme points on a continuum rather than dichotomous processes.

In sum, our study delineates the similarities and divisions between neural correlates of metacognitive monitoring and control. Ultimately, understanding the link between monitoring and control could inform interventions such as metacognitive training in conditions including brain injury (Fleming et al., 2017), schizophrenia (Moritz & Woodward, 2007) and OCD (Fisher & Wells, 2008). We propose that a full understanding of the

648 relationship between monitoring and control will require a focus on the ways in which
649 distinct metacognitive signals are integrated and selectively routed to appropriate acts of
650 metacognitive control.
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929 **Author contributions**

930 AB and SJG designed the research, collected and analyzed the data, and wrote the
931 manuscript. AB prepared the figures. Both authors read and approved the final manuscript.

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933 **Figure Legends**

934 Figure 1: A) Model of metamemory proposed by Nelson & Narens (1990). The arrows
935 indicate the flow of information. B) Example of a typical MetaM miniblock: Participants
936 were presented with a target color and had to rate how confident they were that they would
937 remember this color later on. It was then revealed whether or not they were allowed to use a
938 reminder for the current miniblock (in this case, the fixation dot took on the target color for
939 the duration of the ongoing task). The ongoing task was a shape discrimination task where
940 participants had to judge whether an array of colored shapes was on average a circle or
941 square. The miniblock ended unpredictably with the target color, which participants were
942 instructed to respond to using a different key. The analysis window for the fMRI analyses is
943 highlighted in yellow. C) Two example blocks showing how participants were alternatingly
944 presented with one Baseline miniblock and then four miniblocks of the current metacognitive
945 rating condition (MetaM or MetaC), shown in different colours. The height of the rectangles
946 reflects the approximate length of the miniblocks, their shading and angle the offloading
947 condition. D) Design matrices for the within-category classifications (first two panels from
948 the right) and cross classifications (second two panels from the right). Lighter colors denote
949 beta images modelling the lower half of ratings in the block in question, whereas darker
950 colors denote higher ratings. Please note that in this example the participant began the
951 experiment with the MetaM condition, but that approximately half of our sample started in
952 the opposite order for balancing reasons. Note also that an inverse relationship between
953 MetaC and MetaM is expected in the cross-classification analysis, hence the ordering of high
954 vs. low MetaC (dark vs. light red) has been flipped in the cross classifications.

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956 Figure 2: A) Target detection accuracy across the range of twelve target colors, placed
957 equidistant in RGB space. Only trials without a reminder were included and the data were

averaged across conditions (metacognitive monitoring and metacognitive control). The thick black line indicates the sample average, whereas thinner lines represent individual participants. B) Placement of the cursor in the Baseline condition relative to the marked position on the scale (shown in red). Each black line indicates the data from a single participant. C) Target detection accuracy as a function of miniblock condition (Metacognitive Monitoring and Metacognitive Control) and offloading condition (Own Memory and Reminder) as a raincloud plot (Allen et al., 2019). The distributions depict the densities of the participant-wise accuracy averages for each condition. The boxplots show the median and interquartile range of the data and the lines represent the individual observations.

Figure 3: A) Participants' ratings of Metacognitive Monitoring (low to high confidence) and Metacognitive Control (high to low need for a reminder; to match orientation of the confidence scale) showed a similar pattern across the twelve different colors placed equidistant in RGB space. B and C) Histogram of the B) ratings and C) rating RTs pooled across all participants as a function of rating type. D) Metacognitive ratings as a function of objective accuracy and condition shown as participant-wise averages (left panels) and correlations (right panels). MetaM = metacognitive monitoring; MetaC = metacognitive control.

Figure 4: A) and B) show the regions of significant signal change in the contrast of (MetaM + MetaC) > Baseline. A) Significant results were plotted on sagittal ($x = -3$), coronal ($y = 27$) and axial ($z = 23$) views of the skull-stripped, mean, normalized structural image. B) Three-dimensional renderings of results on right hemisphere, left hemisphere, and superior views. C) Percent signal change for both metacognitive rating conditions in comparison with the Baseline condition, in regions of interest (ROIs) defined by the contrasts shown in Table 2.

MetaM = metacognitive monitoring; MetaC = metacognitive control; r = right; l = left; MFG = middle frontal gyrus; IFG = inferior frontal gyrus; SFG = superior frontal gyrus; SMA = supplementary motor area. Error bars indicate +/- within-subject confidence intervals (95%) according to Morey (2008).

Figure 5: A) and B) show the regions of significant signal change in the contrast of Baseline > (MetaM + MetaC). A) Significant results were plotted on sagittal ($x = 0$), coronal ($y = -20$) and axial ($z = 0$) views of the skull-stripped, mean, normalized structural image. B) Three-dimensional renderings of results on right hemisphere, left hemisphere, and superior views. C) Percent signal change for both metacognitive rating conditions in comparison with the Baseline condition, in regions of interest (ROIs) defined by the task-negative contrasts shown in Table 3. MetaM = metacognitive monitoring; MetaC = metacognitive control r = right; l = left; SMA = supplementary motor area; MTG = middle temporal gyrus; ITG = inferior temporal gyrus; OcG = occipital gyri. Error bars indicate +/- within-subject confidence intervals (95%) according to Morey (2008).

Figure 6: A) and B) show the above-chance decoding accuracy maps for the condition-specific classification analyses (blue: train on MetaM, test on MetaM; red: train on MetaC, test on MetaC; yellow: train on MetaC, test on MetaM). A) Significant results were plotted on sagittal ($x = -5$), coronal ($y = 7$) and axial ($z = 43$) views of the skull-stripped, mean, normalized structural image. B) Three-dimensional renderings of results on right hemisphere, left hemisphere, and superior views. C) and D) show the above-chance decoding accuracy maps when all four classification analyses were averaged (condition-blind decoding). C) Significant results were plotted on sagittal ($x = -18$), coronal ($y = 38$) and axial ($z = 3$) views of the skull-stripped, mean, normalized structural image. D) Three-dimensional renderings of

1008 results on right hemisphere, left hemisphere, and superior views. E) Above-chance
1009 classification accuracy for all four classification analyses (trained and/or tested on MetaM
1010 and MetaC, respectively) in regions of interest (ROIs) defined by a condition-blind selection
1011 contrast that averaged across all four analyses, listed in Table 5. MetaM = metacognitive
1012 monitoring; MetaC = metacognitive control, r = right; l = left; SFG = superior frontal gyrus;
1013 MFG (medial frontal gyrus). Error bars indicate +/- within-subject confidence intervals
1014 (95%) according to Morey (2008).

1015 **Tables**

1016 Table 1: List of experimental conditions.

	Baseline	MetaM	MetaC
Proportion	20% (32 partial + 32 full = 64 miniblocks)	40% (64 partial + 64 full = 128 miniblocks)	40% (64 partial + 64 full = 128 miniblocks)
Delayed intention	/	Target color	Target color
Rating	Cursor placement	Very unconfident to very confident	Sure reminder to sure own memory
Reminders	/	50% (random)	based on moving median rating cut- off

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1018 Table 2: Regions of increased signal in the MetaM and MetaC conditions, relative to the

1019 Baseline condition. MetaM = metacognitive monitoring; MetaC = metacognitive control; l =

1020 left; r = right.

Contrast	Label	Laterality	Peak voxel MNI co- ordinates	k_E	p_{FWE} cluster- corrected	Z_{max} at peak level
(MetaM + MetaC) > Baseline	Occipital and parietal cortex (calcarine cortex; cuneus; precuneus;	right and left	30, -55, 5	1338	< 0.001	5.14

	lateral ventricles; all regions both l and r)					
	Middle frontal gyrus	right	42, 32, 44	345	< 0.001	4.94
	Inferior and middle frontal gyri	left	-42, 20, 26	802	< 0.001	4.68
	Superior and middle frontal gyri	right	27, 62, 5	152	0.002	4.49
	Supplementary motor area	left	-6, 23, 44	117	0.009	4.27
	Angular gyrus	left	-57, -55, 44	150	0.003	4.16
	Pre- and postcentral gyri	right	18, -28, 65	75	0.046	4.08
	Angular gyrus	right	57, -58, 44	87	0.028	4.05

1021

1022 Table 3: Regions of decreased signal in the MetaM and MetaC conditions, relative to the
1023 Baseline condition. MetaM = metacognitive monitoring; MetaC = metacognitive control; l =
1024 left; r = right.

Contrast	Label	Laterality	Peak voxel MNI co-ordinates	k_E	p_{FWE} cluster-corrected	Z_{max} at peak level
Baseline > (MetaM + MetaC)	Cingulate and paracingulate cortices; SMA (supplementary motor area; all regions both r and l)	right and left	3, 2, 35	311	< 0.001	5.99
	Supramarginal gyrus	right	60, -19, 35	809	< 0.001	5.96
	Supramarginal gyrus	left	-66, -28, 35	1249	< 0.001	5.86
	MTG and ITG (middle and inferior temporal gyri); OcG (occipital gyri)	left	-45, -61, 8	534	< 0.001	4.93
	MTG and ITG (middle and inferior temporal gyri);	right	57, -55, -4	508	< 0.001	4.92

	OcG (occipital gyri)					
	Anterior cingulate gyrus	right	3, 32, -4	560	< 0.001	4.61

1025

1026 Table 4: Clusters of above-chance classification accuracy in the four classification analyses.

1027 MetaM = metacognitive monitoring; MetaC = metacognitive control; l = left; r = right.

MVPA	Label	Laterality	Peak voxel MNI co-ordinates	k_E	p_{FWE} cluster-corrected	Z_{max} at peak level
MetaM (low vs. high confidence)	Anterior cingulate gyrus	left	-3, 17, 26	58	< 0.001	4.57
	Parietal occipital sulcus	left	-18, -85, 41	310	< 0.001	4.51
	Central sulcus	right	21, -28, 53	90	< 0.001	4.51
	Superior parietal lobule; superior occipital gyrus; cuneus; precuneus	right	24, -70, 50	404	< 0.001	4.43

	Supplementary motor area (both l and r)	right	15, 14, 44	149	< 0.001	4.10
	Occipital fusiform gyrus	left	-33, -67, -19	80	< 0.001	3.94
	Calcarine cortex; cuneus (all regions both l and r)	left	-6, -67, 14	43	0.003	3.89
	Superior corona radiata	left	-24, -13, 32	38	0.006	3.75
	Precentral gyrus	left	-45, 2, 35	26	0.046	3.69
MetaC (low vs. high need for a reminder)	Occipital pole	left	-9, -100, 14	93	< 0.001	4.09
	Lateral occipital cortex	right	36, -73, 5	28	0.029	4.08
	Superior parietal lobule	left	-12, -67, 53	50	0.001	3.79
	Superior frontal gyrus		0, 29, 50	31	0.017	3.63

	(medial segment)					
	Middle temporal gyrus	right	57, -52, -4	32	0.014	3.58
MetaC → MetaM	Superior and middle frontal gyri	left	-21, 11, 62	52	< 0.001	4.14
MetaM → MetaC	/	/	/	/	/	/

1028

1029 Table 5: Clusters of above-chance classification accuracy in the condition-blind classification

1030 analyses.

Label	Laterality	Peak voxel MNI co-ordinates	k_E	p_{FWE} cluster-corrected	Z_{max} at peak level
Occipital pole	right	15, -94, 11	90	0.002	4.54
Occipital pole	left	-24, -91, -1	321	< 0.001	4.51
Middle occipital gyrus	left	-30, -70, 26	89	0.002	4.47
Parietal cortex (superior parietal lobule; precuneus)	right	18, -55, 59	115	< 0.001	4.22
Superior frontal gyrus	left	-12, 17, 44	114	< 0.001	4.12

Superior and middle frontal gyri; precentral gyrus	left	-27, 8, 62	121	< 0.001	3.96
Parietal cortex (superior parietal lobule; precuneus)	left	-15, -70, 44	91	0.002	3.65

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