# Retrospective confidence judgments across tasks: domain-general processes underlying metacognitive accuracy

Audrey Mazancieux[1]

Stephen M. Fleming[2,3]

Céline Souchay[1]

Chris J.A. Moulin[1]

[1] LPNC CNRS 5105, Grenoble Alpes University, France

[2] Wellcome Centre for Human Neuroimaging, University College London, London, UK

[3] Max Planck UCL Centre for Computational Psychiatry and Ageing, University College London, London, UK

**Corresponding Author**

Audrey Mazancieux

1251 avenue Centrale, St Martin d'Hères

38040 Grenoble FRANCE

audrey.mazancieux@gmail.com

**Word count (without method and result):** 1930 words

## Abstract

Is metacognition a general resource shared across domains? Previous research has documented consistent biases in confidence judgments across tasks. However, the ability to discriminate between correct and incorrect answers (metacognitive sensitivity) is often held to be domain-specific, based on non-significant correlations across domains. Such null findings may be due to low statistical power and differences in task structure or performance, thereby masking a latent domain-generality in metacognition. We examined across-domain correlations in bias and sensitivity in a large sample (N=181). Participants performed four two-alternative-forced-choice tasks (episodic memory, semantic memory, executive function, and visual perception) with trial-by-trial confidence judgments. We found significant correlations between metacognitive biases across tasks. By applying a hierarchical Bayesian model to estimate cross-task covariance, we found significant correlations in metacognitive efficiency (meta-*d'/d'*) across tasks, even for pairs of tasks in which first-order performance was not correlated. This suggests a domain-general resource supporting metacognitive sensitivity in retrospective confidence.


**KEYWORDS:** metacognition, metamemory, monitoring, confidence judgments, domain-general processes

Metacognition refers to the ability to monitor and control cognitive processes (Flavell, 1979). It is often studied with reference to memory (e.g. Nelson & Narens, 1991) but has also recently been quantified for other domains such as visual perception (e.g., Song et al., 2011) decision making (e.g., Yeung & Summerfield, 2012) and motor tasks (e.g., Simon & Bjork, 2001). A critical research question therefore concerns the cross-domain organisation of such metacognitive evaluations of cognition. A domain-general view of metacognition proposes that people use a common resource when they evaluate their performance across different types of tasks. In contrast, a domain-specific account proposes that there are different metacognitive processes at play in different tasks.

By leveraging individual differences it is possible to adjudicate between these two proposals. According to the domain-general view, people who have accurate judgements for one task should also make accurate judgements for another. In contrast, if metacognition relies on domain-specific processes, we would expect such abilities to be uncorrelated. The focus of this paper is to investigate this issue using retrospective confidence judgements (RCJs). RCJs are a self-evaluation of certainty in a given response and are appropriate for addressing the question of domain-generality, as they can be applied to decisions made across a variety of tasks.

In the current study, we focus on assessing the domain-generality of both metacognitive bias and sensitivity, two measures which map onto two different aspects of metacognition. Metacognitive bias refers to the overall magnitude of a judgment, such as whether an observer has a tendency to report high or low confidence, irrespective of their performance. Metacognitive sensitivity refers to the ability of a person to discriminate between different levels of performance, such as correct or incorrect trials (Fleming & Lau, 2014).

Previous research using RCJs has provided equivocal findings for metacognitive sensitivity. Whereas few studies have found positive correlations between metacognitive sensitivity for memory and visual perception tasks (McCurdy et al., 2013; Ruby, Giles, & Lau, 2017), a majority concluded in favour of domain-specificity due to non-significant correlations (Baird, Cieslak, Smallwood, Grafton, & Schooler, 2015; Baird, Smallwood, Krzysztof, Gorgolewski, & Margulies, 2013; Fitzgerald, Arvaneh, & Dockree, 2017; Morales, Lau, & Fleming, 2018). Regarding structural MRI data, distinct cerebral areas correlating with individual variation within two tasks has been observed, also supporting the possibility of neurofunctional independence between domains (Baird et al., 2013; Baird et al., 2015; McCurdy et al., 2013). Specifically, metacognitive sensitivity in a visual perception task has been related to the volume and function of lateral anterior prefrontal cortex (aPFC), whereas metacognitive sensitivity in a memory task is associated with the structure and function of precuneus and medial aPFC. Accordingly, lesions to aPFC have been shown to selectively affect visual perceptual sensitivity while sparing sensitivity on the memory task (Fleming, Ryu, Golfinos, & Blackmon, 2014).

However, a recent meta-analysis of cross-domain correlations in metacognitive sensitivity pointed to a heterogeneous pattern of domain-generality (Rouault, McWilliams, Allen, & Fleming, 2018). Although there was an overall cross-domain correlation between different perceptual tasks (e.g. visual, auditory, tactile; see for instance Ais, Zylberberg, Barttfeld, & Sigman, 2016, or Faivre, Filevich, Solovey, Kühn, & Blanke, 2018) there was equivocal evidence for domain-generality across visual perception and memory tasks. Moreover, it was noted that drawing conclusions about domain-specificity relies on accepting the null hypothesis of no correlation, which is problematic if individual experiments are underpowered to detect a correlation. In addition, it was recognised that cross-domain correlations may also be biased by inconsistencies in the sensitivity index calculated in these studies and variability in task structure.

A first important consideration is the method used to assess metacognitive sensitivity. Different techniques are often used to compute sensitivity which makes it difficult to compare results across studies. Moreover, several of these indexes (such as gamma correlation or area under the Type 2 ROC) do not control for the effect of task performance (Fleming & Lau, 2014), and spurious correlations in metacognitive sensitivity may emerge between domains that are driven by variation in first-order task performance, rather than metacognitive capacity (Rouault et al., 2018). One recent measure that achieves this control is metacognitive *efficiency*, meta-d'/d'. The meta-d' framework models the relationship between performance and metacognition using signal detection theory (SDT). Meta-d' is defined as the Type 1 *d'* that would lead to the observed type 2 ROC curve in the absence of noise or imprecision in confidence estimates (Maniscalco & Lau, 2012). Metacognitive efficiency is then defined as the level of metacognitive sensitivity (meta-d') of a subject *relative* to the subject's actual Type 1 performance. By estimating meta-d' in a Bayesian hierarchical framework (Fleming, 2017) it is possible to directly estimate covariance in metacognitive efficiencies across domains.

A second possible explanation for inconsistencies between results of previous studies is that different task designs have been used in different domains. For instance, several studies have compared metacognitive sensitivity between 2AFC perceptual tasks and yes/no recognition memory tasks. As recently suggested (Ruby et al., 2017), these differences in task structure may obscure across-domain correlations in metacognitive ability, particularly given potential asymmetries in metacognitive ability for yes and no responses (Kanai, Walsh, & Tseng, 2010; Meuwese, van Loon, Lamme, & Fahrenfort, 2014). Here we focus on comparing between different 2AFC tasks which are appropriate for fitting an equal-variance meta-d' model.

Unlike for metacognitive sensitivity, there is greater agreement in previous literature that metacognitive bias is relatively stable across tasks. People tend to be overconfident in their judgments of general knowledge (Lichtenstein & Fischhoff, 1977) and visual perception (Baranski & Petrusic, 1994; Song, et al, 2011), and this degree of confidence is correlated across tasks (Ais et al., 2016). Moreover, the hard-easy effect – overestimation in difficult tasks and underestimation in easy tasks – has also been found in both types of task (e.g., Baranski & Petrusic, 1995). In sum, while previous studies support a domain-generality in metacognitive bias, both neuroimaging and behavioural findings, albeit in small samples, remain equivocal about the domain-generality of metacognitive sensitivity.

The aim of the present study was to compare metacognitive judgments across four different 2AFC cognitive tasks and to ask whether correlations in bias and/or sensitivity are indicative of a common underlying process of metacognition. As noted above, it remains possible that an absence of correlations regarding metacognitive sensitivity is explained by a lack of statistical power, as the sample sizes of previously mentioned studies ranged from 23 to 52 participants. To test a correlation hypothesis, it has been suggested that ' … there are few occasions in which it may be justifiable to go below $n$ = 150' to obtain stable and reliable correlations (Schönbrodt & Perugini, 2013, p.10). Here we employ a large sample (N = 181) based on a priori power calculations and compute the covariance of meta-d'/d' estimates in a hierarchical Bayesian framework, thereby maximizing the sensitivity of our analysis approach to detect shared variance across domains.

## Method

### Participants

The current experiment was conducted in the Laboratoire de Psychologie et Neurocognition (LPNC) in Grenoble, France, and included 181 young adults (*M* = 20.01, *SD* = 3.13; 84% of women) recruited through an advertisement at the Grenoble-Alpes University. We estimated the required sample size according to Schönbrodt and Perugini (2013) using an expected correlation of 0.4 between metacognitive sensitivity on a memory and a perceptual task (McCurdy, et al., 2013). The authors explained that 'the true correlation strength uncontaminated by outlier influence, although significant, is likely to be lower than the *r* value of 0.471' (p.4), hence our more conservative estimate of 0.4. According to Schönbrodt and Perugini (2013), for a correlation of 0.4 and 80% of power in psychology, correlations begin to be stable for 181 participants. All participants were native French speakers and reported having a normal or corrected-to-normal vision. The study was preregistered on the Open Science Framework (https://osf.io/b5ype/).

**Materials and procedure**

The entire procedure included four cognitive tasks: an episodic memory task, a semantic memory task, an executive functioning task, and a visual perception task. See Figure 1 for examples and a schematic representation. The episodic memory task begun with an encoding phase in which participants were presented 40 unrelated pairs of words for 2500ms duration in a randomized order. Words were extracted from the French Lexique database (New, Pallier, Brysbaert, & Ferrand, 2004) according to the following criteria: nouns or adjectives with six letters, two syllables, and between 20 to 100 occurrences per million. During the test phase, participants performed a 2AFC task where they had to decide which one of the two target words was associated with the cue presented in the first phase. Distractors were other words extracted from Lexique according to the same criteria as targets and cues. These 2AFC decisions in this task, and the following, are referred to as the 'first order' task

In the semantic memory task, participants performed a series of 2AFC decisions for French general knowledge questions. Based on a pretest, half of questions were selected as easy and the other half as difficult in order to increase the variability of confidence judgments.

The visual perception task was akin to the one used by Fleming et al. (2014) and consisted of two circles each containing dots presented for 700ms. Participants responded as to which one of the two circles contained more dots. One of the two circles always contained 50 dots and the other had less or more than 50 dots, randomly defined on each trial. Stimuli were created using a plot function in R software. For each stimulus the number of dots was randomly defined – between 25 and 49 for stimuli with fewer dots and between 51 and 75 for stimuli with more dots.

The fourth task consisted of an attention, flexibility and working memory (executive function) task. Participants were presented a letter-number sequence of five symbols for 1s. Half of these sequences had three letters and two numbers and the other half had two letters and three numbers (e.g., 7A5N2). Participants chose which one of the two presented responses corresponds to the sum of all numbers and letters (in the example above the correct answer would be 14AN).

All four tasks comprised 40 trials each and had similar response requirements. The position of the correct answer was randomly assigned and the order of the four tasks was randomised for all participants. To begin each trial participants pressed the "space" bar. For the first-order decision, participants had to press the "s" letter to select the lefthand answer and the "l" letter to select the righthand answer. Figure 1 provides a summary of the four tasks.

After each response on each of the four tasks, participants were asked to evaluate how confident they were in their answer. The scale ranged from 0% of confidence (minimum confidence) to 100% (maximum confidence) and they could answer 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% by pressing the corresponding number (e.g., 0 for 0%; 1 for 10%) and the letter “c” for 100%. It was explained to the participants that 0% confidence signified a guess response. There was no time limit for either first-order decisions or confidence judgments and participants were not asked to respond as quickly as possible; however we measured decision time in an exploratory analysis.

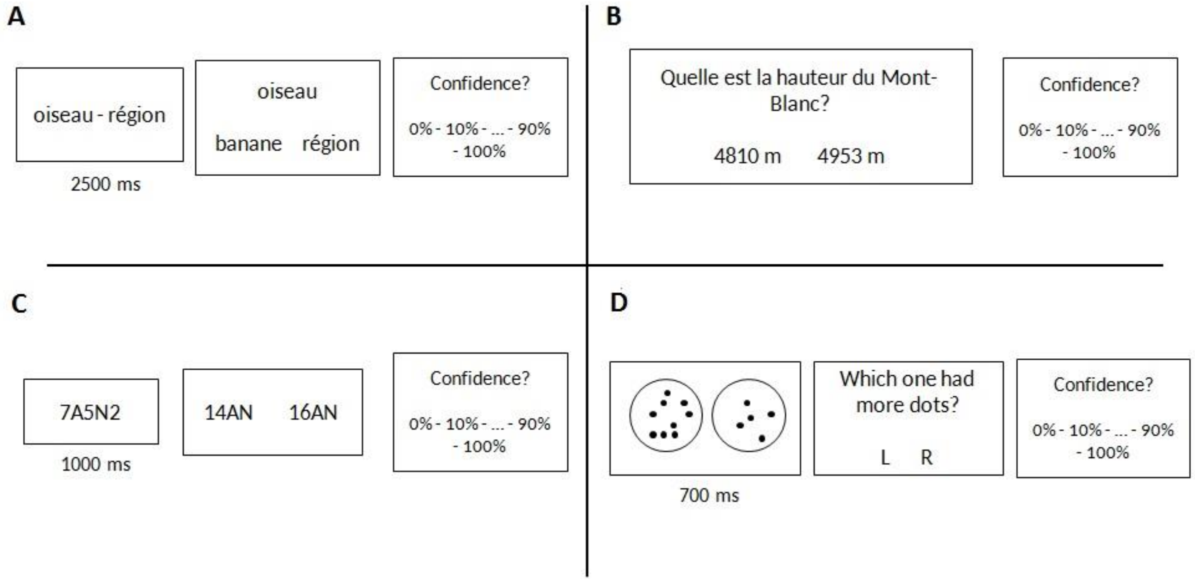



**Figure 1**. Summary of the four tasks. (A) Episodic memory task. (B) Semantic memory task. (C) Working memory/attention task (executive functioning). (D) Visual perception task – real stimuli included between 25 and 75 dots.

**Data and statistical analyses**

As described above, we focussed on both metacognitive bias and metacognitive sensitivity. After data collection was complete, we reasoned that there was some ambiguity in the absolute meaning of the scale label 0% confident, given that chance level in 2AFC tasks is 50%. Contrary to what we pre-registered, we therefore decided to measure metacognitive bias by the average confidence level rather than by the comparison between the percentage of successful trials and the average confidence rating of each task (i.e., absolute accuracy), which depends on subjects interpreting 0% confidence as 50% performance (chance).

Sensitivity was estimated as metacognitive efficiency (meta-d'/d') instead of the area under the Type 2 receiver operating characteristics (ROC) curve. In Type 1 SDT, d' refers to the ability to discriminate between different states of the world (i.e., signal and noise). This parameter can be calculated as d' = z(hits) − z(false alarms),where z is the inverse of the cumulative normal distribution function, hits are the proportion of 'signal' responses when signal is present, and false alarms are the proportion of 'signal' responses when noise is present. In Type 2 SDT, the sensitivity parameter of interest is the ability to discriminate between correct and incorrect responses, rather than signal and noise. Meta-d' refers to the Type 1 d' that would give rise to the observed confidence distributions in the absence of noise or imprecision in the ratings. By modelling the relationship between Type 1 and Type 2 performance (the more information available in the Type 1 task, the more sensitive Type 2 confidence ratings will be), meta-d' quantifies the sensitivity of confidence ratings to performance in units of *d'* (Maniscalco & Lau, 2012). Because *d'* and meta-*d'* are in the same units, they can be compared which allows derivation of a measure of metacognitive efficiency, controlling for task performance. If this measure (Mratio; meta-d' / d') is close to 1, then metacognitive efficiency is optimal under the SDT model.

Here we used a recent hierarchical Bayesian framework (Fleming, 2017) to estimate meta-d' at the group level (HMeta-d). This allows a more accurate estimation of subject-level parameters by allowing the group-level estimates to constrain subject-level fits, and more stable group-level estimates by limiting the impact of single-subject estimates with high uncertainty on the group. Fleming (2017) showed in simulation that HMeta-d was able to recover stable group-level parameter estimates with as few as 50 trials per subject, which was not the case when averaging single-subject maximum likelihood fits. This framework is also particularly useful to test the question of the domain-generality of metacognition since it can also be used to estimate covariance between estimates in a hierarchical framework.

To extend the model, each subject's log metacognitive efficiency (log(meta-*d'*/*d'*)) in the four tasks (M1, M2, M3, M4) was specified as a draw from a multivariate Gaussian:

$$[\log(M1_s)\,\log(M2_s)\,\log(M3_s)\,\log(M4_s)] \sim N\left(\begin{bmatrix}\mu_{M1}\\ \mu_{M2}\\ \mu_{M3}\\ \mu_{M4}\end{bmatrix}, \begin{bmatrix} \sigma^2{}_{M1} & \rho_{M1M2}\sigma_{M1}\sigma_{M2} & \rho_{M1M3}\sigma_{M1}\sigma_{M3} & \rho_{M1M4}\sigma_{M1}\sigma_{M4} \\ \rho_{M1M2}\sigma_{M1}\sigma_{M2} & \sigma^2{}_{M2} & \rho_{M2M3}\sigma_{M2}\sigma_{M3} & \rho_{M2M4}\sigma_{M2}\sigma_{M4} \\ \rho_{M1M3}\sigma_{M1}\sigma_{M3} & \rho_{M2M3}\sigma_{M2}\sigma_{M3} & \sigma^2{}_{M3} & \rho_{M3M4}\sigma_{M3}\sigma_{M4} \\ \rho_{M1M4}\sigma_{M1}\sigma_{M4} & \rho_{M2M4}\sigma_{M2}\sigma_{M4} & \rho_{M3M4}\sigma_{M3}\sigma_{M4} & \sigma^2{}_{M4} \end{bmatrix}\right)$$

Priors were specified as follows:

$$\mu_{M1}, \mu_{M2}, \mu_{M3}, \mu_{M4} \sim N(0, 1)$$

$$\sigma_{M1}, \sigma_{M2}, \sigma_{M3}, \sigma_{M4} \sim \mathrm{InvSqrtGamma}(0.001, 0.001)$$

$$\rho_{M1M2}, \rho_{M1M3}, \rho_{M1M4}, \rho_{M2M3}, \rho_{M2M4}, \rho_{M3M4} \sim \mathrm{Uniform}(-1, 1)$$

*N* is a normal distribution with mean and standard deviation as parameters. $\mu_M$ and $\sigma_M$ refer to the mean and the standard deviation of log(Mratio). $\rho_{MiMj}$ is the correlation coefficient for log(Mratio) between tasks *i* and *j*.

The HMeta-d toolbox (https://github.com/metacoglab/HMeta-d) uses Markov chain Monte Carlo (MCMC) sampling to estimate posterior distribution over model parameters using JAGS (Plummer, 2003). We modified the HMeta-d code to allow estimation of parameters in R using rjags. As in the HMeta-d toolbox, we discarded early samples of the posterior distributions and ran three chains in order to diagnose convergence problems. Convergence diagnostics were computed with the 'coda' package using the 'potential scale reduction factor' $\hat{R}$ (Gelman & Rubin, 1992). Raw data, model and analysis scripts are available in OSF (https://osf.io/b5ype/). Significance of group-level parameters was estimated by calculating whether the 95% highest density intervals (HDIs) on the posterior distributions of the correlation coefficients $\rho_{MiMj}$ overlapped with zero, which is a Bayesian analogue of a frequentist confidence interval since it is the smallest interval containing 95% of the MCMC samples (Kruschke, 2014).

We complemented the HMeta-d analyses with non-hierarchical Pearson's r correlations and paired t-tests. For paired t-tests, outliers were detected using 3 tests: Leverage, RSS and Cook's distance. When necessary, Bonferroni correction was applied.

## Results

### Type 1 performance

We assessed task performance using Type 1 d'. This index was calculated for each participant and each task (see Figure 2A for mean and confidence intervals). For these analyses Bonferroni correction was used providing a significance threshold of $\alpha = 0.05/6 = 0.008$. Paired t-tests showed that performance on the executive function task ($M = 2.58$; $SD = 0.74$) was better than the episodic memory task ($M = 1.84$; $SD = 0.88$), $t(180) = 9.42$, $p < .001$, $d = 0.70$, semantic memory task ($M = 1.19$; $SD = 0.60$), $t(180) = 22.71$, $p < .001$, $d = 1.69$, and visual perception task ($M = 0.92$; $SD = 0.39$), $t(180) = 30.26$, $p < .001$, $d = 2.25$. The episodic memory task was also better performed than the semantic memory task, $t(180) = 9.32$, $p < .001$, $d = 0.69$, and the visual perception task, $t(180) = 13.09$, $p < .001$, $d = 0.97$. Finally, the semantic memory task was better performed than the visual perception task, $t(180) = 4.98$, $p < .001$, $d = 0.37$.

We next examined intersubject correlations in first-order performance across tasks. Table 1 summarises Pearson correlation coefficients between *d'* values. These analyses revealed a positive correlation between episodic and semantic memory performance, $r = 0.23$, $p = .002$. Executive function performance was also positively correlated with semantic memory performance, $r = 0.27$, $p < .001$, and visual perception performance, $r = 0.21$, $p < .001$. However, correlations between other task performance pairings (visual perception and episodic memory; executive function and episodic memory; semantic memory and visual perception) were not significant after correcting for multiple comparisons.

**Table 1**. Pearson correlation coefficients, confidence intervals, and p values for correlations in task performance between pairs of tasks. Alpha threshold is .008.

| | Performance (d') | | | |
|---|---|---|---|---|
| | Episodic memory | Visual perception | Semantic memory | Executive function |
| Episodic memory | | *r* = 0.04 [-0.11, 0.18] *p* = .638 | ***r* = 0.23 [0.09, 0.37] *p* = .002** | *r* = 0.16 [0.02, 0.30] *p* = .030 |
| Visual perception | | | *r* = -0.08 [-0.23, 0.06] *p* = .258 | ***r* = 0.25 [0.11, 0.39] *p* < .001** |
| Semantic memory | | | | ***r* = 0.25 [0.11, 0.38] *p* < .001** |
| Executive function | | | | |

## Metacognitive bias

Mean confidence judgments were calculated for each participant and each task (Figure 2B). The pattern of result for confidence judgements was similar to that for task performance. Paired t-tests (corrected for multiple comparisons) showed people were more confident overall on the executive function task than the episodic memory task, $t(180) = 10.04$, $p < .001$, $d = 0.75$, the semantic memory task, $t(180) = 18.73$, $p < .001$, $d = 1.39$, and the visual perception task, $t(180) = 18.10$, $p < .001$, $d = 1.35$. The episodic memory task was also judged with higher confidence than the semantic memory task, $t(180) = 4.71$, $p < .001$, $d = 0.35$, and the visual perception task, $t(180) = 6.30$, $p < .001$, $d = 0.47$. Finally, the semantic memory task was judged with higher confidence than visual perception task, $t(180) = 3.37$, $p < .001$, $d = 0.25$.

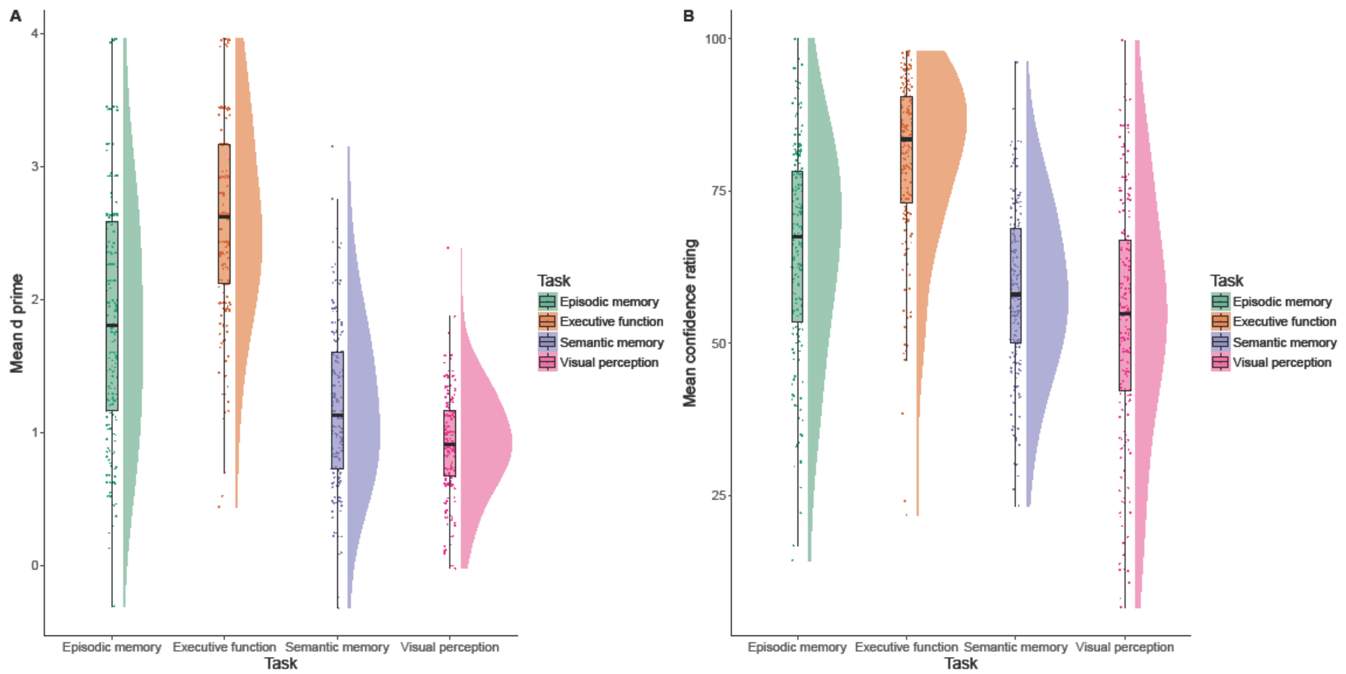



**Figure 2**. (A) Raincloud plots (Allen et al., 2018) for d' for the four tasks. (B) Raincloud plots for confidence level for the four tasks.

In order to estimate domain-general influences on metacognitive bias, we computed correlations between mean confidence levels across tasks (Table 2). We observed a significant correlation between confidence levels across all tasks after correction for multiple comparisons (all $p < .008$ and $r$ ranging from 0.21 to 0.39; the exception was a trend-level correlation between visual perception and episodic memory) suggesting that the more participants report high confidence in one task, the more they report high confidence in another task.

**Table 2**. Pearson correlation coefficients, confidence intervals, and p values for paired correlations of confidence level across tasks. Alpha threshold is .008.

| | Confidence level | | | |
|---|---|---|---|---|
| | Episodic memory | Visual perception | Semantic memory | Executive functioning |
| Episodic memory | | $r$ = 0.19 [0.05, 0.33]<br>$p$ = .009 | **$r$ = 0.34 [0.21, 0.46]<br>$p$ < .001** | **$r$ = 0.21 [0.06, 0.34]<br>$p$ = .005** |
| Visual perception | | | **$r$ = 0.39 [0.27, 0.52]<br>$p$ < .001** | **$r$ = 0.36 [0.23, 0.48]<br>$p$ < .001** |
| Semantic memory | | | | **$r$ = 0.37 [0.23, 0.49]<br>$p$ < .001** |
| Executive functioning | | | | |

**Metacognitive efficiency**

To estimate metacognitive efficiency, we estimated the group meta-*d'*/*d'* ratio for each task (see Figure 3). According to overlaps of 95% HDIs, metacognitive efficiencies were similar for the two memory tasks, which in turn were greater than both the executive function and visual perception tasks (for means and HDIs related to the difference distributions for each comparison see table 3). However, executive function metacognitive efficiency was also greater than visual perceptual metacognitive efficiency.

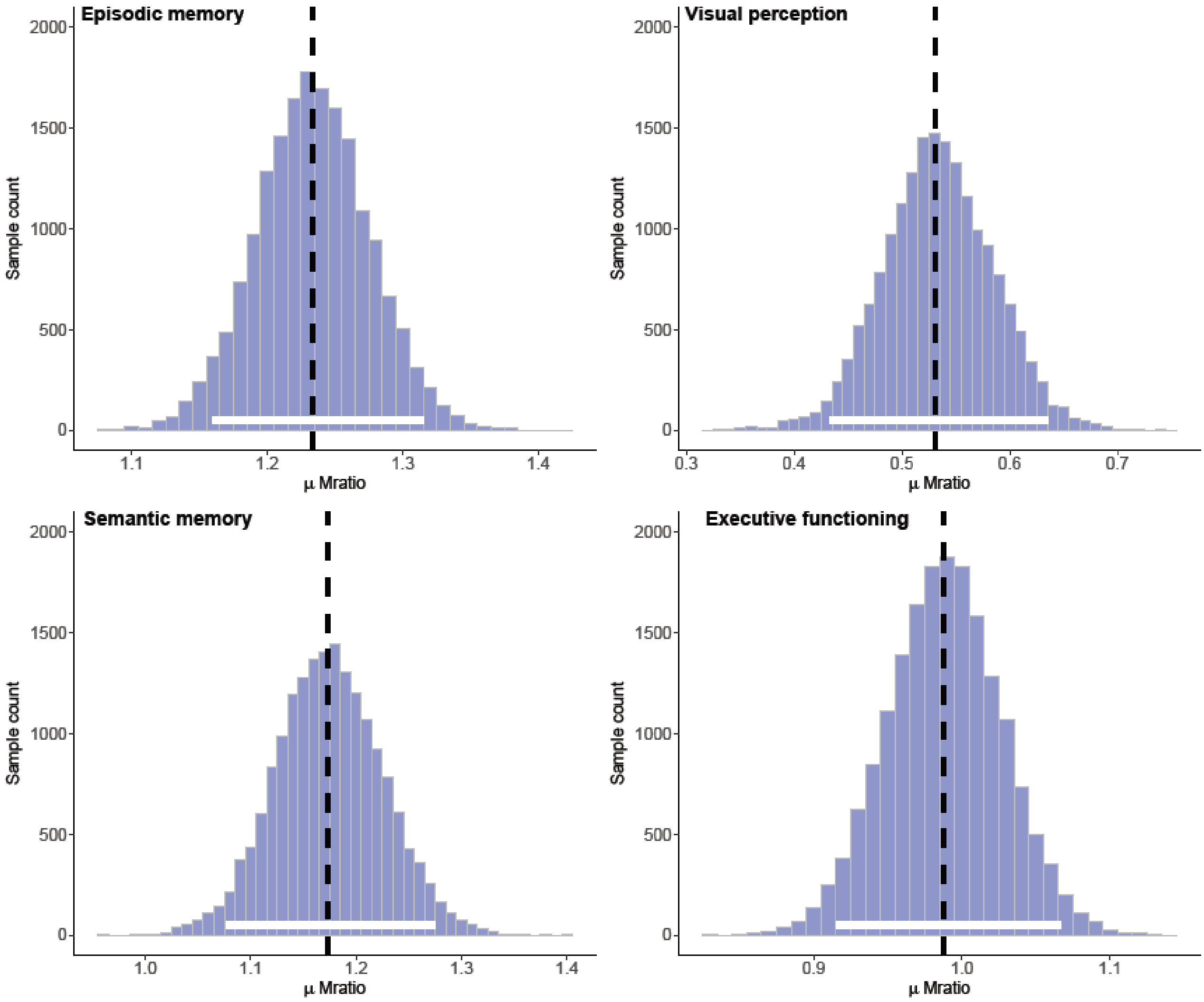
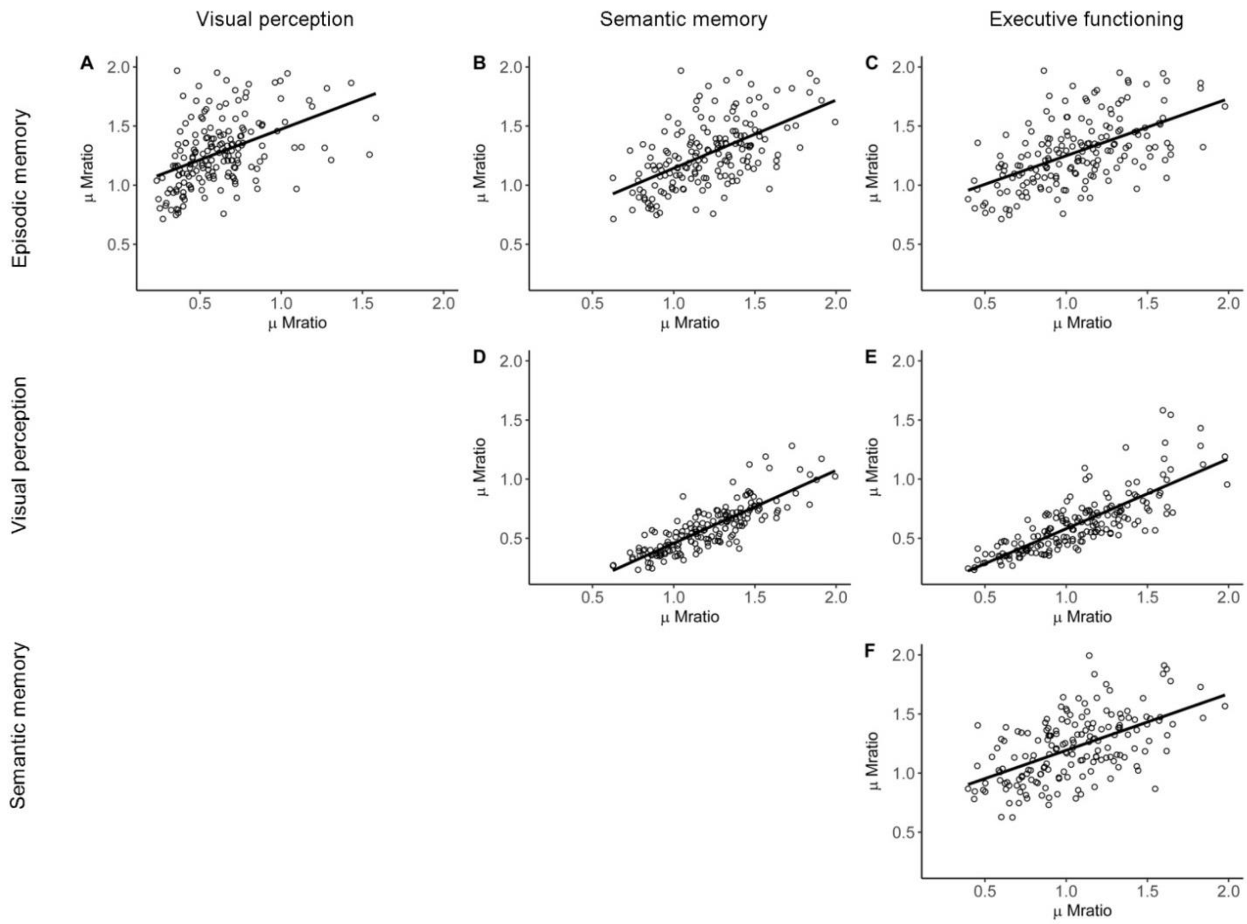



**Figure 3**. Posterior μ Mratio (meta-*d'*/*d'* ratio) distributions for the episodic memory, visual perception, semantic memory and executive functioning tasks.

**Table 3**. Means and HDIs of the posteriors of the difference between μ Mratio distributions for each task pairing. Only the difference distribution between episodic memory and semantic memory overlaps 0.

| | Difference distributions | | | |
|---|---|---|---|---|
| | Episodic memory | Visual perception | Semantic memory | Executive function |
| Episodic memory | | **0.84** [0.72, 0.97] | 0.05 [-0.01, 0.11] | **0.22** [0.17, 0.28] |
| Visual perception | | | **0.79** [0.68, 0.91] | **0.62** [0.51, 0.75] |
| Semantic memory | | | | **0.17** [0.11, 0.23] |
| Executive function | | | | |

In order to evaluate domain-general contributions to metacognitive efficiency, we estimated the covariance of efficiency values across all four tasks within the hierarchical model. Critically, 95% HDIs on the posterior correlation coefficients for 5 out of 6 task pairings did not overlap zero (see Figure 4) suggesting substantial covariance in metacognitive efficiency across domains. This was also the case for task pairings for which we did not observe correlations in task performance (e.g. visual perception and semantic memory; Table 1), suggesting it is unlikely to be an artefact of covariance in first-order capacity. Only the HDI for the correlation between visual perception task and episodic memory task ($\rho = 0.28$; HDI = [-0.03, 0.60]) overlapped zero.


Visual perception
Semantic memory
Executive functioning
Episodic memory
Visual perception
Semantic memory
A
B
C
D
E
F
μ Mratio
μ Mratio

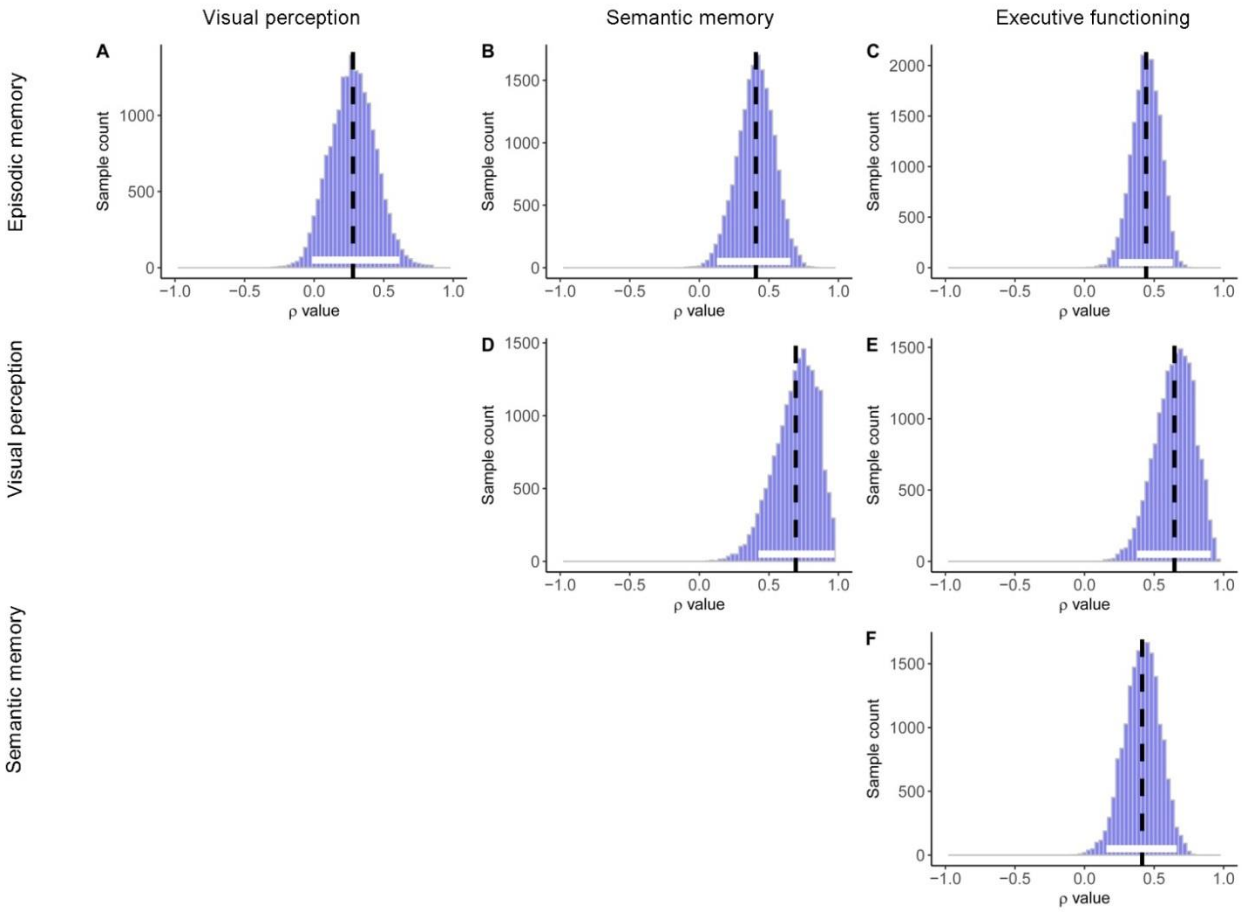

Visual perception
Semantic memory
Executive functioning
Episodic memory
Visual perception
Semantic memory
A
B
C
D
E
F
Sample count
ρ value

**Figure 4**. (A) Single-subject parameter estimates from the hierarchical model of meta-*d'/d'* and Pearson correlations between meta-*d'/d'* estimates across the four tasks. (B) Posterior distributions over ρ for each entry in the covariance matrix determining the correlations between meta-*d'/d'* across the four tasks.

## Discussion

The present study compared RCJs across four cognitive tasks in order to evaluate domain-general and domain-specific processes underpinning both metacognitive bias and metacognitive efficiency. Our study goes beyond previous studies by using a large sample to increase reliability, employing four distinct 2AFC tasks to avoid problems that arise when comparing different task formats, and using a hierarchical estimation of meta-*d*' (and covariance parameters) that facilitated efficient estimation of group-level covariance parameters.

We reproduced previous findings on the domain-generality of metacognitive bias (e.g., Ais, et al., 2016). Except for a trend between episodic memory and visual perception, we found that the tendency to report high confidence in one task is correlated with the tendency to report high confidence in another task, suggesting domain-general contributions to overall confidence level. These results are in line with the sense of confidence being biased by domain-general contextual factors such as mood (see Ais et al., 2016, for optimism influences on bias) and non-pathological psychiatric traits (see Rouault, Seow, Gillan, & Fleming, 2018, in perceptual decision-making).

Regarding metacognitive efficiency, the lowest Mratio was found for the visual perception task. This result is consistent with previous studies which also find better metacognitive efficiency for memory compared to visual perception (Fleming et al., 2014; McCurdy et al., 2013, Morales et al., 2018).

Our study also allowed us to estimate the extent of across-task stability in metacognitive efficiency, by estimating the parameters of a covariance matrix governing the association between meta-d'/d' values in a hierarchical framework. We found substantial shared variance in meta-d'/d' across tasks, with 5 out of 6 correlation parameters deviating from zero. As the meta-d'/d' measure controls for influences of task performance, this result suggests a substantial shared variance in metacognitive efficiency, and is consistent with a domain-general resource supporting metacognition. Critically, these correlations were obtained even for pairs of tasks that did not show correlations in first-order performance (i.e., for semantic memory and visual perception; for episodic memory and executive function). This suggests that correlations in metacognitive efficiency are unlikely to be driven by covariance in task performance.

The one 95% HDI that did overlap zero, for the correlation between episodic memory and visual perception, still showed a substantial probability mass above zero, suggesting uncertainty around the proportion of shared variance, rather than an absence of correlation (HDI = [-0.03, 0.60]). Although our findings are less clear regarding these two tasks, a recent study (Ruby et al, 2018) suggested a positive relationship between metacognitive sensitivity for short-term memory and visual perception when comparing 2AFC tasks using a large sample size (100 participants) and a larger number of trials (120 trials). The correlation they found was very close to the one we estimated here ($r$ = 0.31 and $r$ = 0.28).

Our results on shared variance in metacognitive efficiency across tasks thus suggest the involvement of common processes in metacognitive sensitivity across domains. Recent work has found common brain areas tracking confidence in recognition memory and visual perceptual metacognition tasks (Morales et al., 2018) supporting the idea that both domain-specific and domain-general processes may influence sensitivity. Our findings are also consistent with a second-order model which proposes that a circuit for second-order inferences may be engaged across domains (Fleming & Daw, 2017) due to aspects of the state space, such as motor responses, being shared across tasks (Faivre et al., 2018). Although some cross-domain cues and processes influencing bias have been identified (as described above), further research should focus on identifying domain-general processes influencing metacognitive efficiency.

To conclude, we find that contrary to previous results, both metacognitive bias and metacognitive efficiency share common resources across domains. This observation of a domain-general signature of metacognitive efficiency was obtained after ensuring that task structures were similar across domains (2AFC), that experimental power was sufficient, and that performance-controlled measures of metacognition were employed (meta-*d'*/*d*'). This lends support to the idea that training metacognitive efficiency in one domain can enhanced metacognitive efficiency in another domain (Carpenter et al., 2018). Such 'transfer effects' on metacognition may have important implications for education and rehabilitation programs as they offer a pathway towards generalized improvements of awareness of abilities (or disabilities). Although domain-general cues have been identified for biases in confidence judgement (i.e., anchoring effects, confirmation bias), the source(s) of domain-generality in metacognitive efficiency has received less attention. Further work should focus on identifying the types of processes which influence metacognitive efficiency across domains.

**Acknowledgments**

This work was in part supported by funding from *Initiative d'Excellence* (IDEX) held by University Grenoble Alpes to AM to support a research visit in SMF's lab. SMF is supported by a Sir Henry Dale Fellowship jointly funded by the Wellcome Trust and Royal Society (206648/Z/17/Z). CM gratefully acknowledges the support of the *Institut Universitaire de France.*

## References


Ais, J., Zylberberg, A., Barttfeld, P., & Sigman, M. (2016). Individual consistency in the accuracy and distribution of confidence judgments. *Cognition*, *146*, 377-386.

Allen M, Poggiali D, Whitaker K, Marshall TR, Kievit R. (2018) Raincloud plots: a multi-platform tool for robust data visualization. PeerJ Preprints 6:e27137v1 https://doi.org/10.7287/peerj.preprints.27137v1

Baird, B., Cieslak, M., Smallwood, J., Grafton, S. T., & Schooler, J. W. (2015). Regional white matter variation associated with domain-specific metacognitive accuracy. *Journal of cognitive neuroscience*, *27*(3), 440-452.

Baird, B., Smallwood, J., Gorgolewski, K. J., & Margulies, D. S. (2013). Medial and lateral networks in anterior prefrontal cortex support metacognitive ability for memory and perception. *Journal of Neuroscience*, *33*(42), 16657-16665.

Baranski, J. V., & Petrusic, W. M. (1994). The calibration and resolution of confidence in perceptual judgments. *Attention, Perception, & Psychophysics*, *55*(4), 412-428.

Baranski, J. V., & Petrusic, W. M. (1995). On the calibration of knowledge and perception. *Canadian Journal of Experimental Psychology/Revue canadienne de psychologie expérimentale*, *49*(3), 397-407.

Carpenter, J., Sherman, M. T., Kievit, R. A., Seth, A., Lau, H., & Fleming, S. (2018). Domain-general enhancements of metacognitive ability through adaptive training. *bioRxiv*, 388058.

Faivre, N., Filevich, E., Solovey, G., Kühn, S., & Blanke, O. (2018). Behavioral, modeling, and electrophysiological evidence for supramodality in human metacognition. *Journal of Neuroscience, 38*(2), 263-277.

Fitzgerald, L. M., Arvaneh, M., & Dockree, P. M. (2017). Domain-specific and domain-general processes underlying metacognitive judgments. *Consciousness and Cognition*, *49*, 264-277.

Fleming, S. M. (2017). HMeta-d: hierarchical Bayesian estimation of metacognitive efficiency from confidence ratings. *Neuroscience of Consciousness*, *2017*(1), nix007.

Flavell, J. H. (1979). Metacognition and cognitive monitoring: A new area of cognitive–developmental inquiry. *American psychologist*, *34*(10), 906-911.

Fleming, S. M., & Daw, N. D. (2017). Self-evaluation of decision-making: A general Bayesian framework for metacognitive computation. *Psychological review*, *124*(1), 91-114.

Fleming, S. M., & Lau, H. C. (2014). How to measure metacognition. *Frontiers in human neuroscience*, *8*, 443.

Fleming, S. M., Ryu, J., Golfinos, J. G., & Blackmon, K. E. (2014). Domain-specific impairment in metacognitive accuracy following anterior prefrontal lesions. *Brain*, *137*(10), 2811-2822.

Kanai, R., Walsh, V., & Tseng, C. H. (2010). Subjective discriminability of invisibility: a framework for distinguishing perceptual and attentional failures of awareness. *Consciousness and cognition*, *19*(4), 1045-1057.

Kruschke, J. (2014). *Doing Bayesian data analysis: A tutorial with R, JAGS, and Stan*. Academic Press.

Lichtenstein, S., & Fischhoff, B. (1977). Do those who know more also know more about how much they know? *Organizational behavior and human performance*, *20*(2), 159-183.

Maniscalco, B., & Lau, H. (2012). A signal detection theoretic approach for estimating metacognitive sensitivity from confidence ratings. Consciousness and cognition, 21(1), 422-430.

McCurdy, L. Y., Maniscalco, B., Metcalfe, J., Liu, K. Y., de Lange, F. P., & Lau, H. (2013). Anatomical coupling between distinct metacognitive systems for memory and visual perception. *Journal of Neuroscience*, *33*(5), 1897-1906.

Meuwese, J. D., van Loon, A. M., Lamme, V. A., & Fahrenfort, J. J. (2014). The subjective experience of object recognition: Comparing metacognition for object detection and object categorization. *Attention, Perception, & Psychophysics*, *76*(4), 1057-1068.

Morales, J., Lau, H., & Fleming, S. M. (2018). Domain-General and Domain-Specific Patterns of Activity Supporting Metacognition in Human Prefrontal Cortex. Journal of Neuroscience, 2360-17.

Nelson, T. O., & Narens, L. (1994). Why investigate metacognition. In J. Metcalfe, A. P. Shimamura (Eds.), *Metacognition: Knowing about knowing* (p. 1-25). MIT press.

New, B., Pallier, C., Brysbaert, M., & Ferrand, L. (2004). Lexique 2: A new French lexical database. *Behavior Research Methods, Instruments, & Computers*, *36*(3), 516-524.

Plummer, M. (2003, March). JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling. *In Proceedings of the 3rd international workshop on distributed statistical computing*, *124*(125), 10-18.

Rouault, M., McWilliams, A., Allen, M. G., & Fleming, S. M. (2018). Human Metacognition Across Domains: Insights from Individual Differences and Neuroimaging. *Personality Neuroscience*, *1*.

Rouault, M., Seow, T., Gillan, C. M., & Fleming, S. M. (2018). Psychiatric Symptom Dimensions Are Associated With Dissociable Shifts in Metacognition but Not Task Performance. *Biological psychiatry*, *84*(6), 443-451.

Ruby, E., Giles, N., & Lau, H. (2017). Finding domain general metacognitive mechanisms requires using appropriate tasks. *bioRxiv*, 211805. https://doi.org/10.1101/211805

Schönbrodt, F. D., & Perugini, M. (2013). At what sample size do correlations stabilize?. *Journal of Research in Personality*, *47*(5), 609-612.

Simon, D. A., & Bjork, R. A. (2001). Metacognition in motor learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *27*(4), 907-912.

Song, C., Kanai, R., Fleming, S. M., Weil, R. S., Schwarzkopf, D. S., & Rees, G. (2011). Relating inter-individual differences in metacognitive performance on different perceptual tasks. *Consciousness and cognition*, *20*(4), 1787-1792.

Yeung, N., & Summerfield, C. (2012). Metacognition in human decision-making: confidence and error monitoring. *Phil. Trans. R. Soc. B*, *367*(1594), 1310-132.