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Retrospective confidence judgements in general-knowledge questions:

Magnetoencephalography correlates

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DA: development of preprocessing and analysis pipeline, data curation, formal analyses, visualization, writing and review.

MA: experiment programming, data collection, writing and review

AL: conceptualization, writing and review.

Abstract

Memory monitoring processes are online assessments of the quality of our retrieval. Despite their importance for cognition, few studies on episodic memory and perceptual discrimination studied their neural dynamics and reported diverse results. Also, research showed increased theta in correct lexical identifications, but its monitoring was not investigated. We used MEG to study the brain activity underpinning memory monitoring of retrospective confidence judgments. 29 participants answered multiple-choice general knowledge questions and rated the confidence of their choice, while MEG was recorded. Mixed-effect linear models in the averaged single-trial responses showed a marginal difference for high versus low confidence answers in left dorso-parietal and occipital sensors at 260-320 ms after the presentation of alternatives. Signal power analysis in the 400-800 ms time window showed differences in theta band for low versus high confidence hits and miss trials. However, no differences were found for high hits and misses, which may reflect that in terms of monitoring, both answers are equal for participants. These results support the findings of increased theta power for correct semantic identification extending them to the monitoring processes.

Keywords: retrospective confidence judgments, semantic memory, MEG, theta-band oscillations.

Magnetoencephalography evidence for semantic memory monitoring

Memory monitoring by means of confidence evaluations on its correctness are the triggers for the implementation of strategies to increase the quality and quantity of memories (Nelson & Narens, 1994). Diverse studies with clinical patients highlight the relevance of memory monitoring in several disorders. For example, schizophrenic patients suffer from confidence gap which impairs their ability to distinguish between correct and incorrect memories, feeding the confusion between real and imagined events (Moritz & Woodward, 2006; Moritz, Woodward, & Chen, 2006; Shimamura & Squire, 1986). Another example can be found in the obsessive compulsive disorder: several authors pointed to a failure of an adequate memory monitoring as the grounds for the very disabling «checking behavior» (Boschen & Vuksanovic, 2007, although see also Radomsky, Dugas, Alcolado, & Lavoie, 2014). Yet, despite the relevance for both health and disease, the particular imprint in the cortical brain activity of this process remains rather unexplored. In this research we aimed to fill this gap in the literature and study the oscillatory activity for the subjective evaluations about a retrieved memory, the so-called retrospective confidence judgments.

Only recently the brain correlates involved in the metacognitive process of prospective and retrospective monitoring have started to be defined. Metamemory judgments can be defined as *prospective* when the estimations are done about how well I consider I will remember an item later, or as *retrospective* when what is measured is how well I think I remembered an item. In prospective memory monitoring studies it has been found a distinctive activation of the medial temporal lobe, ventromedial prefrontal cortex, and dorsomedial prefrontal cortex when participants were requested to make predictions about their future memory for images (Kao, Davis, & Gabrielli, 2005). The research on retrospective memory monitoring points to the prominently activation in the anterior and

dorsolateral prefrontal cortex (Fleming & Nolan, 2012). A recent fMRI meta-analysis focused on the retrospective confidence judgments, collapsing several types of task and experimental materials, pointed to the involvement of a concordant bilateral activation in the parahippocampal gyrus, left middle frontal gyrus, and right amygdala (Martín-Luengo, Zinchenko, Dolgoarshinnaia, & Leminen, 2021). Thus, at least in terms of temporality, the recruitment of neural cortices for making memory monitoring judgments differ (Chua, Schacter, & Sperling, 2009; Fleming & Dolan, 2012; Le Berre et al., 2016; Pannu et al., 2005).

Studies focused on the temporal dynamics of prospective monitoring judgments reflect certain variability in their results depending on the material of research. For example, studies in which a prospective memory task was used, judgments of learning (JOLs), found medial frontal and bilateral posterior positivity associated with JOLs (Müller, et al., 2016; Skavhaug, 2010; Skavhaug, Wilding, & Danaldson, 2010; Skavhaug, Wilding, & Danaldson, 2013; Sommer, Heinz, Leuthold, Matt, & Schweinberger, 1995). However, among these studies with JOLs, those involving visual stimuli (drawings in Muller et al., 2016, and faces in Sommer et al., 1995), also found similar frontal positive and posterior negative slow wave effects which are associated with visual working memory processes (Berti, Geissler, Lachmann, & Mecklinger, 2000; Ruchkin, Johnson, Grafman, Canoune, & Ritters, 1997; Uhl, Goldenberg, Lang, Lindinger, Steiner, & Deecke, 1990.; van Schie, Wijers, Mars, Benjamins, & Stowe, 2005). These results suggests two important points. First, the recruitment of areas linked to memory processes when participants were making judgments about the future, indicate that people try to retrieve similar information and made their judgments in line with the fluency and speed of these “trial” retrievals (Nelson, & Dunlosky, 1991). Thus, it seems that even in the case of making confidence judgments about the future recallability of a piece of information, the specific subserving brain underpinnings of that

future cognitive processes are recruited. And second, it is also important that despite big overlapping, the use of different stimuli includes variability in the cortical brain areas recruited. This indicates that small changes in the stimulus or experimental procedure might vary the results from one study to another.

This divergence of results depending on the type of stimuli have been also found in the oscillatory brain activity related to retrospective memory monitoring. In Wynn, Daselaar, Kessels, and Schutter (2019) participants first underwent an intentional encoding phase in which were presented with a list of words that had to sort as *pleasant* or *unpleasant*. In the later memory test participants completed an old/new recognition task along with a 3-point confidence scale: *not sure*, *a bit sure*, *totally sure*. Oscillatory brain activity results showed that parietal theta power was higher for high-confident hits and correct rejections compared with their low-confident counterparts, and also were found differences in frontal theta power for high-confident correct rejections compared with low-confident rejections. In a follow-up study (Wynn, Kessels, & Schutter, 2020) but with the use of pictures as stimuli, the results widely replicated the previous findings except for some additional differences between high-confidence hits vs misses and high-confident correct rejections and false alarms that were not detected in the previous study. Yet, despite the differences between these two experiments in which the only thing that changed was the materials, their results overall suggest that retrospective confidence judgments in episodic memory are reflected in differences in the oscillatory activity in both, parietal and frontal areas between high and low confidence options. These results were interpreted as, whereas the differences in the frontal theta power might indicate the activity of the control processes reacting to novelty (Lee, Lee, Kim, & Jung, 2014), the differences in the parietal activity align with the idea of memory evidence accumulation linked to the subjectively perceived memory confidence (Klimesch, et al 2005). That is, the more evidence we collect in relation to a particular piece of information, the

stronger the trace-strength become and consequently the higher the subjective confidence evaluations (Busey, Tunnicliff, Loftus, & Loftus, 2000; Higham, Luna, & Bloomfield, 2012).

To the authors knowledge there is no published research with a focus on the oscillatory activity of the retrospective confidence judgments for semantic memory. Tulving (1972) described two different types of declarative memory: episodic and semantic memory. Episodic memory refers to the retrieval of information of events. Regardless of the nature of the stimuli, words-semantic, pictorial or acoustic, if the presentation of this stimuli can be located, for example, at the beginning of the experimental session, what we are measuring is episodic memory. Semantic memory, however, refers to the general knowledge we have about the world. Despite that episodic and semantic memory are usually studied as different types of memory and that relay on different brain areas (medial temporal lobe and hippocampus for episodic memory, Cabeza & Nyberg, (2000); left lateral temporal lobe for semantic memory, Dalla Barba, Parlato, Joert, Samson, & Pappata, (1998), they are intrinsically interrelated (Menon, Boyett-Anderson, Schatzberg, & Reiss, 2007). Indeed, a recent fMRI research showed that there is a by-default overlapping of the left inferior prefrontal cortex towards a dorsal-posterior region (Prince, Tsukiura, & Cabeza, 2007) for both types of memories and that some other semantic-memory areas are also recruited during episodic retrieval when the episodic information requested is heavily semantic rooted. In summary, semantic and episodic memory rely in different but overlapping brain areas, thus, their associated processes, as their monitoring, could perform similarly.

The present research

To study the neural activity of the memory monitoring for semantic knowledge we run a study where participants answered general knowledge questions with four alternatives and rated the confidence in the accuracy of their selection inside a MEG. The lack of research directly comparable to our research questions prevent us to stablish strong hypotheses. Yet,

considering the close relationship between the episodic and semantic memory processes, we expected certain similarity with the results by Wynn's et al (2019; 2020), that is, frontal and dorso-parietal differential brain oscillatory activity for high and low confidence answers.

Methods

Participants. Thirty two volunteers (14 females, $M_{age} = 21.9$, $SD = 2.27$) completed the experiment. All participants were native Russian-speakers, right-handed, had normal or corrected-to-normal vision, reported no neurological or psychological disorders, and met the requirements to be tested in MEG. The analyses reported here are from 28 participants (13 females, $M_{age} = 21.5$, $SD = 2.21$). Four participants were excluded because of a large amount of artifacts in their recordings. Before the experiment, all participants gave informed consent and provided information about their completed education (graduated = 2; undergraduates = 15, high school = 11) and time of sleep (mean time of sleep = 7.1 hours). All participants were rewarded in accordance with the university paying rules (250 rubles/hour). The study was approved by the ethical committee of the National Research University Higher School of Economics.

Stimuli. One hundred twenty nine multiple-choice general knowledge questions with four answer alternatives were selected from a validated database (Martín-Luengo et al, 2020). The questions fell into one of four knowledge topics: Natural Sciences (36), Geography (31), History (22), Culture (40) and were chosen to range uniformly on the difficulty scale. Only questions that were possible to be split into three syntactically meaningful segments were selected. Subsequently, questions that led to direct-access answers (Luna, Martín-Luengo, & Brewer, 2015), either rated with 0 or 100 confidence, were discarded on a per-subject level. These levels of confidence reflect the absence of engagement in considering the potential answers because either the participant is totally sure she does know/not know the answer, or

is entirely sure about her choice. Thus, these questions are qualitatively different from the rest, can distort the results, and should not be included.

Procedure. After digitization of head-shape, location of head position coils, and placing electrodes for electrooculogram and electrocardiogram, participants were moved to the magnetically shielded room with the MEG machine. They were placed into the MEG chair and were given a 5-button controller box to use during the experiment. Participants were instructed to minimize their movement during recording sessions.

Before the experiment, resting state was recorded with open and closed eyes (3 minutes each). The experiment started with instructions and a practice session of 5 trials for which the answers were not included in the analysis. After the clarification of any doubt about the procedure, the experiment started (see Fig. 1 for experimental timeline procedure). Participants' task was to read the questions and select the correct answer. Then, they had to rate their confidence in the correctness of their choice on an 11-points scale (0% - totally unsure, 100% - totally sure). Participants completed three blocks of 43 questions randomly assigned and randomized order avoiding to have more than two questions of the a priori same confidence level (i.e., only two questions classified with low confidence in Martín-Luengo, et al, 2020). Questions and answers were presented in white font on a black screen placed 60 cm apart from the participant. The size of the stimuli was within a 5 degrees visual angle. The placement of the alternatives on the screen was counterbalanced for each participant.

The experimental trial started with the fixation cross presented as a visual cue for 1000 ms with ± 10 ms jitters. Then 3 segments of the question, each on a separate screen, were shown one after another for the self-paced reading: the screen with each subsequent question segment appeared after the button press. After the final question segment, the fixation cross was presented once again for 1000 ms with ± 10 ms jitters during which the participants were instructed to fixate their vision of the cross and think the answer. Once the

fixation cross disappeared, a screen with four alternatives placed at the corners was presented. The location of the alternatives was randomized between participants. Participants selected the correct alternative by reading it out loud, after which they changed the screen with a button press. Next, the participants were presented with the 11-points confidence scale (0-100%, 10%-ranged). They reported the level of confidence in the given answer by saying it aloud and then with the button press they were moved to the next trial. The onset of the screens with a fixation cross, question segments, answers, and confidence were marked with event triggers.

The experiment lasted ~1.5–2 h including the preparation, instructions, practice, and the experimental part. Between blocks participants had 2 minutes breaks to rest. Experiment was programmed in the E-prime software (Psychology Software Tools, Inc., Sharpsburg, USA). After the experiment, participant's answers were grouped into three levels of confidence: 10-20-30 for low confidence, 40-50-60 for medium confidence, 70-80-90 for high confidence.

MEG data acquisition. MEG data were acquired inside a magnetically shielded room (AK3b, Vacuumschmelze GmbH, Hanau, Germany) using a dc-SQUID Neuromag™ VectorView system (Elekta-Neuromag, Helsinki, Finland) comprising 204 planar gradiometers and 102 magnetometers. Data were sampled at 1000 Hz and filtered with a band-pass 0.03-333 Hz filter. The participants' head shapes were collected with a 3Space Isotrack II System (Fastrak Polhemus, Colchester, VA) by digitizing three anatomical landmark points (nasion, left and right preauricular points) and additional randomly distributed points on the scalp. During the recording, the position and orientation of the head were monitored by four Head Position Indicator (HPI) coils. The electrooculogram (EOG) was registered with two pairs of electrodes located above and below the left eye and at the

outer canthi of both eyes for the recording of vertical and horizontal eye movements respectively.

Data preprocessing. Data preprocessing was performed with a custom pipeline based on MNE-python and MNE-BIDS software packages (Appelhodd et al, 2019; Gramfort, et al., 2013). Complete data preprocessing pipeline was made publicly available at <https://github.com/dmalt/metacognition>. For preprocessing data were organized according to the BIDS standard (Appelhof, et al, 2019). Preprocessing pipeline included the following steps:

1. Maxwell filtering. For Maxwell filtering we manually inspected all the recorded data and marked bad channels and segments. Then we applied the Signal Space Separation algorithm (Taulu & Kajola, 2005), with bad channels and segments excluded.
2. Downsampling. To reduce the size of data we merged all three blocks for each participant together, filtered the data in 1-100 Hz frequency band and downsampled it from 1000 to 500 Hz
3. Artifacts removal with ICA. Cardiac, oculographic, muscle and some non-biological artifacts were removed using ICA decomposition. The decomposition was computed using the ‘fastica’ method keeping 99% of the variance in components via the MNE-python software package. To control for ICA’s intrinsic randomness and make the procedure reproducible we fixed the random seed. In the process we saved the components’ time series and topographies for further manual inspection. The components that appeared to be related to cardiac, oculographic, muscular or sensor artifacts were removed from the data.
4. Bad segments annotation and epoching. After the ICA artifacts removal the data were inspected manually once again and all the segments with remaining artifacts were annotated as bad. Such annotations were saved alongside the data. For epoching, the

data were split into 2-second epochs with 0 marking the middle of the epoch (answer alternatives onset) and -1 s denoting the onset of the fixation cross. All the epochs intersecting manually marked bad segments were discarded.

Analysis

We aimed at exploring the effect of subjective confidence and answer correctness on the participants' brain activity without a clear *a priori* hypothesis. The traditional analysis path suggests some sort of averaging procedure over trials for each subject and then performing a regression analysis to look for dependence between the recorded MEG activity and behavioral scores. However, in our case the number of trials which fall into the low confidence group (confidence score in 10-30% range) and the number of trials in the high confidence group (70-90% range) after discarding bad data segments differed substantially for most participants rendering this type of analysis incorrect (see Fig. 2).

For that reason, we chose to perform a single-trial analysis of such dependence using linear mixed effects models (LMM) which overcome the problem of statistical dependence between trials coming from the same participant. We performed linear mixed effects models analyses using the *statsmodels* v.0.13.0 Python package (Seabold & Perktold, 2010).

Single-trial cluster amplitude. Since the parameter space for MEG recordings is very large and we did not have a clear a-priori hypothesis for the evoked responses in relation to the metacognitive behavioral scores, we looked into ways to narrow down the search space to get a smaller number of features to compare between conditions. Namely, we looked for spatio-temporal clusters of difference between low and high-confidence conditions on single trials.

Cluster-based permutation test is a powerful nonparametric tool (Maris, & Oostenveld, 2007), which allows for mitigating multiple comparisons problem when testing

batches of time and sensor points via leveraging similarity between adjacent points. Such an effect is achieved by the means of merging close-by data points with similar activity into clusters and then comparing their summary statistics to the Monte-Carlo-generated null distribution.

In our case, cluster-based permutation test per se is not directly applicable due to the aforementioned difference in the number of trials and the associated statistical complications with computing the evoked responses. However, the by-product of such analysis, namely the spatio-temporal clusters of difference between conditions, can be used as hints for potential latency and location of the conditions dissimilarity, which can be further analyzed with more suitable techniques.

To provide such guidance, we took epochs from all subjects and merged them into a single pool, for now making no account for the dependence of epochs coming from the same subject. We then split epochs into low (10-30% conf. score) and high confidence (70-90%) groups and ran a cluster-based permutation test, using one-way F-test for pointwise statistic (Maris, & Oostenveld, 2007) on single-trial amplitudes to obtain sensor-level clusters of difference between low and high confidence trials. We then averaged the amplitudes for each trial over all sensor and time points in the resulting difference cluster and ran a random-intercept mixed-effects model for the computed cluster averages taking confidence, correctness and their interaction as independent variables and subject id as a random effect.

Amplitude and theta-power analysis for parietal sensors. Following the analysis path from Wynn et. al., 2019, we focused on the 400-800 ms time window, post answers onset and took the parietal group of sensors. Please, note that the time 0 in the figures corresponds to the onset in which the answers was displayed. First we looked at evoked responses and theta power averaged across the chosen sensors.

For evoked responses we constructed an independent categorical variable with three levels: high confidence (70-80-90%) correct answer (HIGH HIT), low confidence (10-20-30%) correct answer (LOW HIT) and incorrect answer (MISS). For each participant we then averaged trials within each of three levels for condition as well as within selected sensors and time points. After the averaging we ended up with 84 data points (28 subjects times 3 condition levels) and ran the regression analysis with mixed effects model (random intercept, subject IDs being a random effect).

To compute power in theta bin we used Welch's method (Welch, 1967) with an effective window size of 260 ms and averaged the computed spectrum within the 4-8 Hz bin. We then used single trial power to fit mixed effect model with categorical condition variable constructed the same way as for evoked responses.

Note that gradiometers and magnetometers might provide opposed directionalities of an effect because they measure different physical properties and spatial structure signals. For this reason we report only the surface location and time windows of the differences but not their directionality due to their ambiguity.

Results

Behavioral results. We split each of the 129 presented questions into knowledge categories and registered the distribution of participants' answers in regards to the answers accuracy and confidence (See Fig. 3). Total mean accuracy and confidence across all questions combined were 0.49 and 55.1 respectively. From the visual inspection of Figure 3 we can notice that the boundaries for accuracy are higher than the expected for a multiple choice test with four alternatives of answers where the odds of choosing the correct alternative by chance is .25. In relation to the confidence values, it is interesting to see certain general underconfidence (lower range of confidence values compared to their accuracies)

except for those questions related to Geography. In general, the results replicate those from the database from where the questions were selected (Martín-Luengo, et al, 2020).

Single-trial average amplitude. Running cluster-based spatio-temporal permutation test on gradiometers revealed a dorso-parietal cluster of sensors for which the amplitude in the low-confidence trials is higher than that for the high-confidence trials in the 260-320 ms time window post answer alternatives onset ($p = 0.04$, 100 permutations), see Fig.4.

The cluster-based spatio-temporal permutation test in this case on magnetometers revealed a frontal cluster of sensors showing differences between low and high conditions ($p = 0.01$, 100 permutations). For sanity check we searched for similar cluster for gradiometers, re-running cluster-based permutation test with acceptance level for p-value increased to $p = 0.3$, 100 permutations. We found the corresponding gradiometers cluster indeed, but with a somewhat different spatial structure, which might be due to the differences in the spatial structure of the magnetic field itself compared to its gradient, and much lower $p = 0.27$, 100 permutations, see Fig. 5.

The significant results of these clusters provide possible hints for timing and location of differences between low and high confidence conditions. Thus, the next step it to analyse their cumulative activity taking into account intra-subject correlations by the means of linear mixed effects models. The analysis with mixed-effects linear model for the dorso-parietal gradiometers cluster (Fig. 4) revealed a marginally significant effect of confidence on the within-cluster-average amplitude ($p = 0.66$, $T = -1.835$), see Table 1.

For the frontal cluster (Fig. 5) mixed model revealed a significant impact of confidence on the average amplitude both for magnetometers ($p = 0.002$, $T = 3.161$) and gradiometers ($p = 0.01$, $T = -2.569$).

Amplitude and theta-power analysis for parietal sensors (Wynn's et al., 2019; 2020 analysis). Mixed model for evoked responses averaged across parietal sensors within a

400-800 ms time window did not show any significant effects. Model summary is presented in Table 3.

At the same time, single-trial amplitudes show significant difference between HIGH and LOW-HIT conditions for gradiometers ($p = 0.046$, $T = 1.996$), see Table 4.

For theta power HIGH-HITS differed significantly from LOW-HITS for magnetometers ($p = 0.038$, $T = -2.073$) and marginally significant for gradiometers ($p = 0.066$, $T = -1.842$). The model summaries for both sensor types can be found in Table 5. Note that linear mixed effect model assumptions in this case do not hold (see Fig. 13, 14). We addressed this issue by applying log-transformation to the data, which fixed the residuals distributions (see Fig. 15 for magnetometers case). However, the transformed data failed to reveal any significant dependencies between condition and the data for both types of sensors.

Discussion

The goal of this study was to investigate the neural brain activity related to semantic memory monitoring. To this end, participants answered general knowledge questions and rated the confidence they had on the correctness of their selected answers. We found both, early frontal and dorso parietal differences linked with the high and low participants' confidence judgments. The frontal differences appeared right after the onset of the answers which support previous research that link this result with the evaluation of novelty of the alternatives (Lee, et al., 2014). The dorso-parietal differences appeared right after the onset of the confidence scale which has been suggested to be linked to the evidence accumulation evaluation for producing memory monitoring judgments (Klimesch, et al 2005). Thus, our results are in line with the previous results in episodic memory monitoring extending them to semantic memory monitoring. Yet, we found some divergences that might be explained because of the different type of memory that was monitored, episodic vs semantic, and the different type of method used, EEG and MEG.

Our results on the sensor level analyses are quite aligned with the results from episodic memory monitoring (Wynn, et al., 2019; 2020) in terms of timing and localization, since we both found an early frontal and dorso-parietal differences related to confidence levels. However, when we replicated their analysis considering the different types of answers, the parallelism is not such direct. One parsimonious reason for this discrepancy is the calculation we made of the signal detection theory indices (Macmillan & Creelman, 2004). Our participants answered general knowledge questions with four alternatives, that is, they were presented with both, correct and incorrect answers on each trial. Consequently, the only two components of the signal detection theory we could calculate were hits (selection of the correct answer) and misses (selection of an incorrect answer). The methodological approach that would allowed a more directly comparison our results with Wynn's et al would have require two elements: questions presented without correct alternative and a two-step procedure for answering. In this two-steps procedure participants should had answered whether the correct answer was among the alternatives, and in the case of affirmative answer, to indicate the correct one. In this way, for those question without correct alternative the computation of false alarms (yes answer, and selection of an alternative) and correct rejections (no answer, and no-selection) would have been possible. However, despite the experimental viability, this procedure is non-viable to be run in MEG since we would need the double of the amount of questions we used which it would have doubled the time-length of the experiment (up to 4 hours) with the negative consequences this might have in participant's performance. Yet, despite the not-possible direct comparison of both studies, the results do not contradict each other.

As developed in the introduction, the few studies on memory monitoring brain correlates no matter which methodology used, provide slightly different results. This differences arise from comparing either different types of memory, episodic or semantic

(episodic memory, Cabeza & Nyberg, (2000); semantic memory, Dalla Barba, et.al, (1998)), temporality of the monitoring judgments (prospective, Kao et al, (2005), vs retrospective, Fleming & Nolan, (2012)), or the stimuli used (words, Skavhaug, et. al, (2010) vs drawings in Muller et al., (2016)). Yet, despite the divergent results it seems that there is a rather high general alignment in results. This links with the debate about the existence (or not) of one unitary monitoring system for all cognitive processes. For decades, the mainstream view within metacognitive research was the proposal of a unique brain entity devoted to the monitoring regardless of the cognitive processes involved (Morales, Lau, & Fleming, 2018). If this was the case, it would not matter the cognitive processes on which the subjective experience was measured because for example both attention and memory cognitive processes would be monitored by the same brain structure. However, even within the same cognitive process, memory, we find divergences.

In this line it is also worth to mention the need to avoid a narrow focus in for example the selection of the power bands to be checked. Basic cognitive processes are interconnected and in very few utterly artificial situations we will use only one of them. For example, when we are encoding a piece of information we use our top-down attentional processes. In an attentional discrimination task we will need to compare the stimuli presented with the target to be detected that previously need to be encoded, and a confidence rating on the perceived accuracy of our discrimination can be made. This retrospective monitoring judgment hypothetically could be subserved by the traditional memory brain correlates since to monitor our performance we need to compare the presented stimuli with a probe target. A recent study focused on the monitoring of attention, concretely in tactile discrimination (Whitmarsh, Oostenveld, Almeida, & Lundqvist, 2017), focused their analyses in the alpha band since it has been repeatedly associated with attentional processes (Klimesch, Sauseng, & Hanslmayr, 2007). They found that the attention ratings, but not retrospective confidence ratings on their

performance, correlated a pre-stimulus alpha power activity. In a similar study also focused in tactile discrimination, it was found correlation of alpha power and mean confidence for correct but not incorrect trials. Unfortunately, these studies did not report information about other power bands, therefore, it remains open the question whether there is some theta-band activity during the discrimination in an attentional task due to the need of contrasting the stimuli presented with the target to be detected. This information would help to understand whether a retrospective confidence judgment is intrinsically linked to the oscillatory activity of the monitored cognitive processes or there is some more general system of monitoring with sub-dependencies.

Finally, the methodology used can provide different results. To a large extent, both EEG and MEG are used to study the temporal dynamics of brain activity but each one measures different things (Lopes da Silva, 2013). Moreover, many studies propose their combined use which emphasizes the divergence of their recordings and their complementarity (Cichy, & Pantazis, 2017; Yosinagasa, et al, 2002). Thus, it is needed to consider the particular methodology use to compare, a priori, similar results.

Limitations

This study also presents some limitations that could be overcome in next experiments. For example, a larger number of questions would have delivered more answers on each confidence level and allowed to compare them. It will be very interesting to explore the differences not only between high and low confidence levels but also for medium confidence levels.

The type of analyses we performed here, concerning linear mixed effect models, is not as conventional for MEG-based studies as for example repeated-measures ANOVA. Although it allowed us to mitigate the effect of the unbalanced design (see Fig. 2) it also produced a number of limitations and technical challenges.

First, our analyses rely on the selection of spatio-temporal region of interest (ROI) with cluster-based permutation test. Such selection is not grounded in any rigorous statistical procedure and is prone to generating spurious clusters due to overestimation of the statistical significance in presence of correlated data (Sainani, 2010). For instance, we have approached the source-space analyses with the same kind of statistical pipeline, which involves finding clusters of potential difference with cluster-based permutation test, but at the very first stage we have found too many significant clusters to comprehend without slipping into multiple comparisons pitfall.

Second, mixed effects models rely on a numerical optimization of the restricted likelihood function which makes them computationally demanding and does not guarantee convergence when a model does not provide good fit to data. In our case this becomes especially problematic since it limits the usage of Monte-Carlo-based techniques for multiple comparisons correction. For instance, to avoid ROI selection we have first approached the analysis with custom cluster-based permutation test for LMM which makes use of T-statistic for fixed effect coefficient (see Supplemental materials), but we discovered that for amplitude analyses LMM fails to converge too often on permuted data. For power analysis however the convergence problem disappeared, but this analysis did not reveal any significant clusters. At the same time we would like to stress out that cluster-based permutation test for LMM requires quite complicated procedure and our tool might need further validation.

Third, from a theoretical standpoint LMMs require a number of assumptions to be met. The most common diagnostic procedure for LMMs involves checking the normality and homoscedasticity of the model's residuals. We have performed these checks visually and we have found that while the amplitude-based models seem to display satisfactory assumptions fit, single-trial theta-power residuals do in fact violate them (see Supplemental materials, fig. 6-15). Thus, although linear mixed models are reported to be robust with regards to the

distribution assumptions violation (Schielzeth, 2020) theta-power results should be interpreted with caution.

In conclusion, we provided the first evidence that the neural brain activity related to the monitoring of semantic memory is at large extend similar to episodic memory monitoring. Our results also contribute to the scarce number of studies on memory monitoring supporting the idea of a general monitoring system, at least, for each cognitive process. Yet, more research is needed because of the large variety of monitoring tasks that can be used and that potentially might have their own peculiarities.

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Figure 1. The timeline of the experiment procedure with steps, time, and triggers sent. The example included the question “How many gallons are contained in one barrel of oil?” and 4 alternatives “a) 42, b) 36, c) 48, d) 54”. Time limits equal to $1000\text{ms} + 10\text{ms}$ jitters were only on fixation crosses, other stages were without time limits. Triggers were sent at: T1 - the onset of the answers screen presentation; T2 - the onset of the confidence screen presentation.

Figure 2. Number of trials falling into the low and high confidence conditions. Blue - high confidence epochs, orange - low confidence epochs.

Figure 3. Accuracy and confidence distribution of questions across different knowledge areas. Each box represents the median with 1-st and 3-d quartiles, Q1 and Q3. Whiskers show minimum and maximum values that fall into 1.5 interquartile distance (IQR) from the quartiles, namely $Q1 - 1.5 \text{ IQR}$, $Q3 + 1.5 \text{ IQR}$. The diamonds show outlier points out of the range.

Figure 4. Cluster of single-trial amplitude differences gradiometers.

Figure 5. Cluster of single-trial frontal amplitude differences for magnetometers (top) and gradiometers (bottom).

Table 1. Mixed effects model summary for the dorso-parietal cluster of single-trial amplitudes (gradiometers). Table shows names and levels for independent variables (leftmost column), the value of the regression coefficient with 95% confidence interval, standard deviation for the estimated regression coefficient and finally, the coefficient's p-value.

Independent variable		Regression coef. (95% CI)	Std. err.	p
Intercept		1.124 (0.166, 2.083)	0.489	0.021
Answer correctness	Wrong	Ref	Ref.	Ref.
	Correct	-0.292 (-0.919, 0.334)	0.32	0.36
Confidence		-0.729 (-1.507, 0.049)	0.569	0.66
Correctness : Confidence interaction	Wrong : confidence	Ref.	Ref.	Ref.
	Correct : confidence	0.703 (-0.413, 1.819)	0.569	0.217
ICC subject		0.32		

Table 2. Mixed effects model summary for the frontal cluster of single-trial amplitudes. Table shows names and levels for independent variables (leftmost column), the value of the regression coefficient with 95% confidence interval, standard deviation for the estimated regression coefficient and finally, the coefficient's p-value.

		Magnetometers			Gradiometers		
Independent variable		Regression coef. (95% CI)	Std. err.	p	Regression coef. (95% CI)	Std. err.	p
Intercept		-0.947 (-2.198, 0.305)	0.639	0.138	-0.167 (0.166, 2.083)	0.203	0.412
Answer correctness	Wrong	Ref	Ref.	Ref.	Ref	Ref.	Ref.
	Correct	-0.446 (-2.021, 1.129)	0.804	0.579	0.023 (-0.919, 0.334)	0.155	0.883
Confidence		3.148 (1.196, 5.100)	0.996	0.002	-0.494 (-1.507, 0.049)	0.192	0.010
Correctness : Confidence interaction	Wrong : conf.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	Correct : conf.	0.234 (-2.570, 3.039)	1.431	0.870	0.092 (-0.413, 1.819)	0.276	0.740
ICC subject		0.05			0.24		

Table 3. Mixed effects model summary for the average evoked responses for parietal sensors in 400-800 ms time window. Table shows names and levels for independent variables (leftmost column), the value of the regression coefficient with 95% confidence interval, standard deviation for the estimated regression coefficient and the coefficient's p-value.

		Magnetometers			Gradiometers		
Independent variable		Regression coef. (95% CI)	Std. err.	p	Regression coef. (95% CI)	Std. err.	p
Intercept		0.466 (-0.142, 1.073)	0.310	0.133	-0.037 (-0.095, 0.021)	0.029	0.209
Condition	HIGH HIT	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	LOW HIT	-0.427 (-0.936, 0.082)	0.260	0.1	0.049 (-0.007, 0.106)	0.029	0.089
	MISS	-0.314 (-0.823, 0.195)	0.260	0.227	0.029 (-0.028, 0.085)	0.029	0.317
ICC subject		0.65			0.54		

Table 4. Mixed effects model summary for the average single-trial amplitudes for parietal sensors in 400-800 ms time window. Table shows names and levels for independent variables (leftmost column), the value of the regression coefficient with 95% confidence interval, standard deviation for the estimated regression coefficient and the coefficient's p-value.

		Magnetometers			Gradiometers		
Independent variable		Regression coef. (95% CI)	Std. err.	p	Regression coef. (95% CI)	Std. err.	p
Intercept		0.515 (-0.083, 1.114)	0.306	0.092	-0.042 (-0.095, 0.021)	0.030	0.162
Condition	HIGH HIT	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	LOW HIT	-0.383 (-1.013, 0.247)	0.321	0.233	0.064 (-0.007, 0.106)	0.032	0.046
	MISS	-0.361 (-0.832, 0.111)	0.240	0.134	0.031 (-0.028, 0.085)	0.024	0.198
ICC subject		0.08			0.08		

Table 5. Mixed effects model summary for the average single-trial theta power for parietal sensors in 400-800 ms time window. Table shows names and levels for independent variables (leftmost column), the value of the regression coefficient with 95% confidence interval, standard deviation for the estimated regression coefficient and the coefficient's p-value.

		Magnetometers			Gradiometers		
Independent variable		Regression coef. (95% CI)	Std. err.	p	Regression coef. (95% CI)	Std. err.	p
Intercept		21.425 (16.0, 26.8)	7.8	< 0.001	0.993 (0.758, 1.227)	0.12	< 0.001
Condition	HIGH HIT	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
	LOW HIT	-2.774 (-5.396, -0.151)	1.338	0.038	-1.03 (-0.212, 0.007)	0.056	0.66
	MISS	-0.083 (-2.044, 1.879)	1.001	0.934	0.005 (-0.077, 0.087)	0.042	0.905
ICC subject		0.39			0.42		

Supplemental materials

Checking linear mixed model assumptions.

There are certain assumptions that need to be met for linear mixed effects concerning the distribution of model residuals, namely:

- residuals must be normally distributed
- homoscedasticity of variance for the residuals must hold
- errors must be independent

To check these assumptions, for each model we checked visually the distribution of errors (Fig. 6 - Fig. 15). We show 4 kinds of diagnostic plots for residuals:

1. Residuals distribution together with fitted gaussian curve, top left
2. Quantile-quantile (Q-Q) plot of residuals against normal distribution, top right
3. Scatter plot for residuals vs fitted values, bottom left
4. Boxplot with residuals distribution across subjects, bottom right.

The former two plots assess normality of the residuals, whereas the latter two assess homoscedasticity and independence of errors. In ideal case we would like to see that the residuals pdf aligns with the gaussian curve for the first plot, that the residuals lay on the theoretical line for the Q-Q curve, that residuals variance, shown on the scatter plot, doesn't show any patterns of uneven distribution with respect to the fitted values and finally, the boxplot should show approximately uniform structure of residuals distribution across subjects.

For figures 6-8 and 11-12 we see satisfactory alignment with the normal distribution and no clear patterns in both scatter and box plots. Although the fit is not perfect, it has been shown that linear mixed models are to a certain degree robust to the deviations from normality (Schielzeth, 2020).

Figures 9-10, which show diagnostic plots for parietal 400-800 ms ERPs also demonstrate quite good fit with the gaussian curve. The boxplots demonstrate a lot of variance in distribution structure across subjects, which is understandable since in this case there are only 3 data points per subject and such estimations can't be considered reliable. We included the boxplots for the sake of completeness.

At the same time, distribution and Q-Q plots for single trial theta-power demonstrate substantial deviation from normality and the scatter plots suggest heteroscedasticity (Fig. 13, 14).

Figure 6. Distribution of residuals for dorso-parietal gradiometers cluster model.

Top left: estimated probability density for errors (solid blue area) and fitted normal distribution (black line), top right: Q-Q plot for errors, bottom left: residuals vs fitted values, bottom right: residuals distribution across subjects.

Figure 7. Distribution of residuals for frontal magnetometers cluster model.

Top left: estimated probability density for errors (solid blue area) and fitted normal distribution (black line), top right: Q-Q plot for errors, bottom left: residuals vs fitted values, bottom right: residuals distribution across subjects.

Figure 8. Distribution of residuals for frontal cluster model (gradiometers).

Top left: estimated probability density for errors (solid blue area) and fitted normal distribution (black line), top right: Q-Q plot for errors, bottom left: residuals vs fitted values, bottom right: residuals distribution across subjects.

Figure 9. Distribution of residuals for parietal sensors ERP (magnetometers). Top left: estimated probability density for errors (solid blue area) and fitted normal distribution (black line), top right: Q-Q plot for errors, bottom left: residuals vs fitted values, bottom right: residuals distribution across subjects.

Figure 10. Distribution of residuals for parietal sensors ERP (gradiometers). Top left: estimated probability density for errors (solid blue area) and fitted normal distribution (black line), top right: Q-Q plot for errors, bottom left: residuals vs fitted values, bottom right: residuals distribution across subjects.

Figure 11. Distribution of residuals for parietal single-trial amplitudes in 400-800 ms time window (magnetometers).

Top left: estimated probability density for errors (solid blue area) and fitted normal distribution (black line), top right: Q-Q plot for errors, bottom left: residuals vs fitted values, bottom right: residuals distribution across subjects.

Figure 12. Distribution of residuals for parietal single-trial amplitudes in 400-800 ms time window (gradiometers). Top left: estimated probability density for errors (solid blue area) and fitted normal distribution (black line), top right: Q-Q plot for errors, bottom left: residuals vs fitted values, bottom right: residuals distribution across subjects.

Figure 13. Distribution of residuals for parietal sensors single-trial theta power (magnetometers). Top left: estimated probability density for errors (solid blue area) and fitted normal distribution (black line), top right: Q-Q plot for errors, bottom left: residuals vs fitted values, bottom right: residuals distribution across subjects.

Figure 14. Distribution of residuals for parietal sensors single-trial theta power (gradiometers). Top left: estimated probability density for errors (solid blue area) and fitted normal distribution (black line), top right: Q-Q plot for errors, bottom left: residuals vs fitted values, bottom right: residuals distribution across subjects.

Figure 15. Distribution of residuals for parietal sensors log-transformed single trials theta power (magnetometers). Top left: estimated probability density for errors (solid blue area) and fitted normal distribution (black line), top right: Q-Q plot for errors, bottom left: residuals vs fitted values, bottom right: residuals distribution across subjects.

Cluster-based permutation test for mixed linear model regression coefficients

To explore the potential induced power effects of confidence we developed a custom tool for cluster-based permutation test for regression coefficients in mixed linear models which can be found at <https://github.com/dmalt/permute>.

To make use of this tool, we performed time-frequency decomposition for each sensor, averaged across frequencies to get the frequency bins of interest (theta, 4-8 Hz, alpha, 8-12 Hz and beta, 13-18 Hz), ran spatio-temporal permutation cluster test, where for point-wise statistic we used t-statistic for significance assessment of regression coefficients in mixed effects linear model.

The particular type of mixed effects linear model was as follows:

- The dependent variable was the power in the frequency bin of interest at the given sensor at the given time point

- The fixed effects were the confidence score (with removed 0 and 100 confidence levels), answer correctness and their interaction
- We took subject as a random effect

To generate the null-hypothesis distribution using Monte-Carlo simulations we randomly permuted confidence and correctness values between trials within each subject destroying the statistical connection between MEG data and behavioral scores. Such analyses however did not reveal any significant clusters.