JNeurosci THE JOURNAL OF NEUROSCIENCE

Research Articles: Behavioral/Cognitive

Sure I'm sure: Prefrontal oscillations support metacognitive monitoring of decision-making

Martijn E. Wokke[1,2,3,4,5], **Axel Cleeremans**[1,2,5] **and K. Richard Ridderinkhof**[3,4]

[1]*Consciousness, Cognition and Computation Group, Université Libre de Bruxelles, 1050, Bruxelles*
[2]*Center for Research in Cognition & Neurosciences, Université Libre de Bruxelles, 1050, Bruxelles*
[3]*Amsterdam Brain and Cognition, University of Amsterdam, 1018, Amsterdam*
[4]*Brain and Cognition, Department of Psychology, University of Amsterdam, 1018, Amsterdam*
[5]*ULB Neuroscience Institute (UNI), Université Libre de Bruxelles, 1050, Bruxelles*

DOI: 10.1523/JNEUROSCI.1612-16.2016

Received: 21 April 2016

Revised: 14 October 2016

Accepted: 4 November 2016

Published: 12 December 2016

Author contributions: M.E.W. and K.R.R. designed research; M.E.W. performed research; M.E.W. analyzed data; M.E.W., A.C., and K.R.R. wrote the paper.

Conflict of Interest: The authors declare no competing financial interests.

The authors would like to thank Sarah L. Knot for helping collecting the data and Simon van Gaal and two anonymous reviewers for their useful comments. A.C. is a research director of the National Fund for Scientific Research. This work was supported by the ABC talent grant to M.E.W., by the ERC advanced grant RADICAL to A.C and by Interuniversity Poles of Attraction (IUAP) grant P7/33 from the Belgian Science Policy Office to A.C.

Correspondence should be addressed to Martijn E. Wokke, Université Libre de Bruxelles, Consciousness, Cognition and Computation Group, Department of Psychology, Avenue Franklin Roosevelt 50, 1050 Brussels Belgium, martijnwokke@gmail.com

Cite as: J. Neurosci 2016; 10.1523/JNEUROSCI.1612-16.2016

Sure I'm sure: Prefrontal oscillations support metacognitive monitoring of decision-making

Abbreviated title: Prefrontal theta oscillations support metacognition

Martijn E. Wokke[1,2,3,4,5*], Axel Cleeremans[1,2,5] & K. Richard Ridderinkhof [3,4]

1. Consciousness, Cognition and Computation Group, Université Libre de Bruxelles, 1050, Bruxelles

2. Center for Research in Cognition & Neurosciences, Université Libre de Bruxelles, 1050, Bruxelles

3. Amsterdam Brain and Cognition, University of Amsterdam, 1018, Amsterdam

4. Brain and Cognition, Department of Psychology, University of Amsterdam, 1018, Amsterdam

5. ULB Neuroscience Institute (UNI), Université Libre de Bruxelles, 1050, Bruxelles

*Martijn E. Wokke
Université Libre de Bruxelles
Consciousness, Cognition and Computation Group
Department of Psychology
Avenue Franklin Roosevelt 50
1050 Brussels Belgium
martijnwokke@gmail.com

Number of pages: 21
Number of figures: 5
Number of words abstract: 210
Number of words introduction: 616
Number of words discussion: 1425

Acknowledgements

The authors would like to thank Sarah L. Knot for helping collecting the data and Simon van Gaal and two anonymous reviewers for their useful comments. A.C. is a research director of the National Fund for Scientific Research. This work was supported by the ABC talent grant to M.E.W., by the ERC advanced grant RADICAL to A.C and by Interuniversity Poles of

Attraction (IUAP) grant P7/33 from the Belgian Science Policy Office to A.C. The authors declare no competing financial interests.

Abstract

Successful decision-making critically involves metacognitive processes such as monitoring and control of our decision process. Metacognition enables agents to adaptively modify on-going behavior and to determine what to do next in situations where external feedback is not (immediately) available. Despite the importance of metacognition for many aspects of life, little is known about how our metacognitive system operates or about what kind of information is used for metacognitive (second-order) judgments. In particular, it remains an open question whether metacognitive judgments are based on the same information as first-order decisions.

Here, we investigated the relationship between metacognitive performance and first-order task performance by recording EEG signals while participants were asked to make a “diagnosis” after seeing a sample of fictitious patient data (a complex pattern of colored moving dots of different sizes). In order to assess metacognitive performance, participants provided an estimate about the quality of their diagnosis on each trial.

Results demonstrate that the information that contributes to first-order decisions differs from the information that supports metacognitive judgments. Further, time frequency analyses of electroencephalographic signals reveal that metacognitive performance is specifically associated with prefrontal theta band activity. Together, our findings are in line with a hierarchical model of metacognition, and suggest a crucial role for prefrontal oscillations in metacognitive performance.

Significance Statement

Monitoring and control of our decision process (metacognition) is a crucial aspect of adaptive decision-making. Crucially, metacognitive skills enable us to adjust on-going behavior and determine future decision-making when immediate feedback is not available.

In the present study, we constructed a “diagnosis task” that allowed us to assess in what way first-order task performance and metacognition are related to each other. Results demonstrate that the contribution of sensory evidence (size, color and motion) differs between first- and second-order decision-making. Further, our results indicate that specifically metacognitive performance is orchestrated by means of prefrontal theta oscillations. Together, our findings point toward a hierarchical model of metacognition.

Introduction

Monitoring and control of our decision process (metacognition [Flavel, 1979; Fleming & Dolan, 2012]) is a crucial aspect of adaptive decision-making. For instance, a doctor who is not very confident about a diagnosis will prescribe additional tests; a tennis player who just executed a drop shot will assess the likelihood of the shot being successful in order to determine her next move. Crucially, such metacognitive skills enable us to adjust on-going behavior and determine future decision-making when immediate feedback is not available. Despite the obvious importance of metacognition, little is know about how our metacognitive system operates, or how first-order performance and metacognition (second-order performance) are related to each other. In particular, it remains an open question whether first- and second-order judgments are based on the same information (Steinhauser & Yeung, 2010; Desender et al., 2016).

On the one hand, metacognitive judgments are often viewed as depending on the very same processes that underpin first-order decisions. From this perspective, the information available for metacognitive computations is directly dependent on the quality and quantity of accumulation of sensory evidence (Kiani & Shadlen, 2009; Kiani et al., 2014). By contrast, dissociations between first- and second-order performance (Weiskrantz et al., 1974; Del Cul et al., 2009; Rounis et al., 2010; Harsay et al., 2012; King & Dehaene, 2014; Hebart et al., 2014; Fleming et al., 2015) suggest that metacognition and first-order task performance are supported by differential (though related) sources of information (Cleeremans et al., 2007; Yeung & Summerfield, 2012; Charles et al., 2014; Maniscalco & Lau, 2016). It has been proposed that dissociations between first- and second-order performance are the result of differences in availability of supporting information (Baranski & Petrusic, 1998; Del Cul et al., 2009; Yeung & Summerfield, 2012; Fleming et al., 2015). Further, hierarchical models of metacognition hold that sensory evidence used for first-order performance becomes susceptible to accrual of noise and signal decay when arriving at the stage where this information is being used by the metacognitive system (Pleskac & Busemeyer, 2010; Maniscalco & Lau, 2016).

Over the last decade, first-order decision-making has been strongly linked to trial-by-trial electrophysiological cortical oscillatory dynamics (Siegel et al., 2012). For instance, recent findings have associated theta band activity with the rate of evidence accumulation and integration (Vugt et al., 2012; Werkle-Bergner et al., 2014), whereas activity in the beta band has been shown to predict behavioral choices (Donner et al., 2007; Donner et al., 2009; Haegens et al., 2011), and seems to be important for maintenance of persistent activity (Engel & Fries, 2010; Siegel et al., 2012; Kloosterman, 2015; Kloosterman et al., 2015). Despite mounting evidence of an intrinsic relationship between first-order decision-making and neural oscillatory activity, however, it remains unknown how oscillatory dynamics relate to second-order decision-making.

In the present study, we constructed a task in which participants were asked to make a "diagnosis" after seeing a sample of fictitious patient data (a pattern of colored moving dots of different sizes). The patterns provided probabilistic information about patient health according to contingencies unknown to the participant; participants were to learn these contingencies (explicitly or implicitly [Cleeremans et al. 1998]) and to diagnose each patient as accurately as possible. On each trial, participants rated both the quality and the reasoning strategy of their decision. Our task design allowed us to assess the relationship between fluctuations in electrophysiological oscillatory activity and changes in first-order decision accuracy, metacognitive judgment adequacy, and strategy judgment. In addition, we were able to test how different sources of sensory evidence (size, color and motion information) contributed to first- and second-order task performance. To capture these behavioral and electrophysiological relationships we applied the multiple regression method (Rousselet et al., 2009; Cohen & Cavanagh, 2011).

Materials and Methods

Participants

Thirty-eight participants (28 females, mean age= 23.1, SD= 6.55) took part in this study for financial compensations. In order to investigate how changes in task accuracy, metacognitive adequacy and metacognitive strategy (Berry & Dienes, 1993; Price & Norman, 2008) related to neural oscillatory activity we focused our analyses on those participants who exhibited variability in both their first- and second-order decisions and metacognitive strategy. We therefore excluded participants i) who performed at chance level throughout the whole experiment, ii) almost exclusively indicated to have made decisions of very poor quality (resulting in less than 50 'high quality decision' trials), and iii) participant who almost exclusively guessed (resulting in less than 50 intuitive and rational trials, see below). Five participants were excluded because of failed EEG recordings. In these participants, we observed excessive noise in more than half of all trials (partially due to our long epoch, see below). A total of nineteen participants were included for further analyses. All participants had normal or corrected-to-normal vision, and all were naïve to the purpose of the experiment. All procedures complied with international laws and institutional guidelines and were approved by the Ethics Committee of the Psychology department of the University of Amsterdam, and all participants provided their written informed consent prior to the experiment.

Task design

Stimuli were presented full screen (1024*768 pixels) on a 17-inch DELL TFT monitor with a refresh rate of 60 Hz. The monitor was placed at a distance of ~90 cm in front of each participant so that one centimeter subtended a visual angle of 0.64°. On each trial a sample of fictive patient data was presented, which consisted of blue, red and green colored circles of different sizes (14, 24 and 34 pixels in diameter) that moved in three different directions (45°, 135° or 315°, see Figure 1) against a white background.

During the experiment one color, one size and one motion direction was indicative of illness (e.g., the color blue, medium size, and motion left upwards). The sample was positive if the presence of a combination of the indicative color, size and motion direction exceeded a certain threshold (i.e., the criterion was set at 160%, see below). The task parameters were based on data from an extensive pilot study, and were set so as to measure trial-by-trial fluctuations in task accuracy, metacognitive adequacy and metacognitive strategy. Metacognitive adequacy was based on decision quality ratings (see below). A high value was awarded when participants rated a correct decision to be a high-quality decision or when an error was rated as being of low quality and vice versa. On each trial, the percentage of each feature (color, motion direction and size) was randomly set between 10-70% (steps of 10%), until the total percentage of each separate feature added up to 100% (e.g., 30% small circles, 40% medium sized circles and 30% large circles). On "positive sample" trials, the percentages were randomly set until the sum of the percentages of the three indicators varied between 160% and 210%. Importantly, participants had to pay attention to all three indicators to perform the task correctly. Paying attention to only one indicator was not sufficient. For instance, a high number of blue circles (e.g., 70%) could belong to a negative sample, depending on the percentage of the other two indicators. The task therefore required participants to conjunctively discriminate between the features.

The stimulus was presented for ~1750 ms, during which the circles were displaced 7 pixels per screen refresh in one out of the three possible directions. At any moment during stimulus presentation a total of 600 circles were on the screen. Each trial started with a blank screen (jittered between 1000-1800 ms, in steps of 100 ms) on which the words ”loading patient data” were centrally presented. After stimulus presentation (~1750 ms) a blank screen (jittered between 1000-1500 ms, with a 50 ms step) was presented to avoid the influence on prolonged evidence accumulation (Yeung & Summerfield, 2012; Hebart et al., 2014), followed by an image of a clipboard (Figure 1) on which “sick” or “exit” had to be ticked by pressing a left or right button (indicating a positive or negative sample, respectively).

Next, participants had to rate how they had arrived at their diagnosis (strategy judgment). Participants could indicate whether (1) their first-order decision was based on a pure guess (like flipping a coin), (2) was made intuitively (pre-reflective, described as the feeling of knowing what to decide without explicitly knowing why [Berry & Dienes, 1993; Price & Norman, 2008]), or (3) rationally (i.e., reflective, knowing what to decide based on explicit knowledge), by pressing the 1, 2 or 3 key respectively. Participants then provided their estimate about the quality of their decision, on a scale ranging from 1 to 5 (by pressing the 1-5 key). Participants were instructed to assign a low value to a diagnosis that they experienced to be of poor quality and a high value to a diagnosis they considered to be of high quality. Participants were encouraged to make use of the whole scale. Finally participants received feedback about their first-order (diagnosis) decision (see Figure 1).

The experiment lasted around 2.5 hours and consisted of 512 trials divided into 8 blocks. After each block, the metacognitive scales (strategic judgment and judgment accuracy) were explained again to make sure the meaning of the scales were properly understood throughout the entire experiment. Within each block, negative and positive samples were presented in pseudo-random order. Stimuli were presented using Presentation (Neurobehavioral Systems).

Behavioral analyses

In order to find out whether first-order decision accuracy and metacognitive adequacy differed depending on strategic judgment we calculated first-order task sensitivity ($d_{a,}$ a variant of da which takes unequal variance into account, see Macmillan & Creelman, 2004), metacognitive sensitivity (meta-d_a) and metacognitive efficiency (meta-d_a – d_a [Maniscalco & Lau, 2012; Fleming & Lau, 2014]), for rational and intuitive decisions and guesses separately. First-order task sensitivity (d_a) and metacognitive sensitivity (meta-d_a) are bias-free measures of the ability to detect a signal from noise (a sick sample in this experiment) and the ability to distinguish between good and bad decisions, respectively (both in units of first-order d_a). By subtracting d_a from meta-d_a (metacognitive efficiency) we were able to determine metacognitive sensitivity relative to different levels of first-order task performance (Fleming & Lau, 2014). The latter is important because metacognitive sensitivity is known to be influenced by first-order task performance (Fleming & Lau, 2014). We performed multivariate repeated measures analyses of variance (MANOVA) on first- and second-order task performance as dependent variables and strategic judgment (with three levels: rational, intuitive and guess) as the independent variabele.

To determine whether different stimulus parameters (size, color and motion) contributed differentially to task accuracy and metacognitive adequacy we performed robust multiple linear regressions, resulting in the following linear equations:

$$Y_1 = INT + b_1 ColorEv + b_2 SizeEv + b_3 MotionEv + b_4 TaskAcc + E.$$

$$Y_2 = INT + b_1 ColorEv + b_2 SizeEv + b_3 MotionEv + b_4 MetaAdeq + E.$$

In this equation, Y_1 is the data vector containing first-order task performance scores, Y_2 is the data vector containing metacognitive adequacy scores, INT is the intercept, and E is unexplained variance. The stimulus parameters ColorEv, SizeEv and MotionEv ranged between 1-7, indicating the amount of evidence (percentage divided by 10) of each indicator (color, size and motion direction, respectively) present on each trial. We rescored decision quality ratings (see above) such that they now reflected the adequacy of the metacognitive judgment (MetaAdeq). A high value was awarded when participants rated a correct decision to be a high-quality decision or when an error was rated as being of low quality; similarly a low value was awarded when an error was rated as a high-quality decision or when a correct was rated as a low-quality decision. This value of metacognitive adequacy could vary between 1-5 (i.e., 5 points were awarded when a correct decision received a 5 point rating or when an error received a 1 point rating; 4 points were awarded when a correct decision received a 4 point rating or when an error received 2 points, etc.). The values for task accuracy (TaskAcc) varied between 0 and 1 (incorrect and correct, respectively). In order to make the TaskAcc predictor less binary, we grouped all trials into 100 bins per participant. We adopted the multiple linear regression method to parcel out variance caused by different experimental settings (e.g., the varying amount of color, motion and size evidence present in the stimulus on each trial) and behavioral variables (e.g., task accuracy or metacognitive adequacy). In this way, the unique contribution of each variable can be observed, controlling for shared variance among the different variables (Cohen & Cavanagh, 2011). To be able to compare b values across participants and between behavioral variables (e.g., between task accuracy and metacognitive adequacy), we standardized b values by scaling the coefficients by their standard deviations. All behavioral analyses were performed using Matlab (Matlab 12.1, The MathWorks Inc.), type 2 SDT scripts (Maniscalco & Lau, 2012: http://www.columbia.edu/~bsm2105/type2sdt/) and SPSS (IBM SPSS Statistics, 22.0).

EEG measurements and analyses

EEG was recorded and sampled at 1048 Hz using a Biosemi ActiveTwo 64-channel system, with four additional electrodes for horizontal and vertical eye-movements, each referenced to their counterpart (Biosemi – Amsterdam, The Netherlands). High-pass filtering (0.5 HZ), additional low-pass filtering (100 HZ) and a notch filter (50 HZ) were used. Next we down-sampled to 512 Hz, after which eye movements were corrected on the basis of Independent Component Analysis (Vigário, 1997). The data was epoched -1 to + 4 sec surrounding stimulus onset. We removed trials containing irregularities due to EMG or other artifacts by visually inspecting all trials. To increase spatial specificity and to filter out deep sources we converted the data to spline Laplacian signals (Cohen, 2014). Subsequently, per participant and per electrode the average of all trials was subtracted from each individual trial to obtain the non-phase-locked power (Kalcher and Pfurtscheller 1995; Donner & Siegel, 2011; Kloosterman et al., 2015). Next we used a sliding window Fourier transform (Mitra and Pesaran, 1999), window length: 400 ms, step size: 50 ms, to calculate the time-frequency representations of the EEG power (spectrograms) for each channel and each trial. We used a single Hanning taper for the frequency range 2–30 Hz (frequency resolution: 2.5 Hz, bin size: 1 Hz [Kloosterman et al., 2015]). Power modulations were characterized as the percentage of power change at a given time and frequency bin relative to baseline power value for that frequency bin. The baseline was calculated as the mean power across the pre-stimulus interval (from -0.3 to 0 s relative to stimulus onset). All signal processing steps were done using Brain Vision Analyzer (BrainProducts) and Matlab (Matlab 12.1, The MathWorks Inc.), **X** code (Cohen, 2014) and Fieldtrip (Oostenveld et al., 2010).

To increase the signal-to-noise ratio and decrease the number of comparisons we used the data from a pilot study (n=19) to pre-select our channels, frequencies and time windows of interest for statistical testing (see Figure 3a-b). The pilot study was identical to the main experiment with the exception that participants did not indicate the quality of their decision on each trial. We created six regions of interest (electrode selections): Occipital, left and right parietal, left + right motor and prefrontal, thereby focusing our analyses on changes in theta (4-6 HZ) and lower beta (13-20 HZ) band activity in an early (0-1 s) and late (2-2.5 s) time window after stimulus presentation (Figure 3b). We performed random-effects analyses by applying paired t-tests (two-tailed) to test whether the mean percentage of power change in each time window for each frequency bin differed significantly from baseline (from -0.3 to 0 s relative to stimulus onset). Because we tested six poolings in each time window and frequency bin, we corrected for multiple comparisons by adjusting the p value by fixing the false discovery rate (FDR) at 0.05 (Benjamini and Hochberg, 1995).

Crucially, in order to study the relationship between theta and beta power modulations and trial-by-trial differences in metacognitive strategy, metacognitive adequacy and task accuracy, a robust multiple regression was computed that estimated parameters for mean power in the above described time windows and frequency bands. This resulted in the linear equation:

$$Y = INT + b_1 StratJudg + b_2 MetaAdeq + b_3 TaskAcc + b_4 ColorEv + b_5 SizeEv + b_6 MotionEv + E$$

Here Y is the data vector (baseline corrected theta or beta power values across trials for each time period), INT is the intercept, $b_{1\text{-}6}$ are regression coefficients, E is unexplained variance, and StratJudg, MetaAdeq, TaskAcc, ColorEv, SizeEv and MotionEv are trial vectors of the participant's strategic judgment ratings, metacognitive judgment adequacy scores, first-order performance scores, and stimulus parameters on each trial. StratJudg (metacognitive strategy judgment) ranged between 1 and 3 (1= guess, 2= intuitive decision, 3= rational decision). We grouped trials again into 100 bins per participant. To be able to compare b values across time, frequencies, poolings, and participants we standardized b values by scaling the regression coefficients by their standard deviations.

Results

Behavior

To test how strategic judgment related to task performance and metacognitive sensitivity we performed a repeated measures MANOVA on d_a, meta d_a and metacognitive efficiency. We found a significant effect of strategic judgment for both d_a ($F(2, 36) = 44.74$ $p < .001$) and meta d_a ($F(2, 36) = 10.52$ $p < .001$), while observing a marginally/non-significant significant effect for metacognitive efficiency ($F(2, 36) = 2.64$ $p= .086$). Participants were better able to distinguish sick from healthy patterns when making rational decisions compared to intuitive and guess trials (ratio-intuitive d_a: $t(18)=7.21$, $p< 0.001$; ratio-guess d_a: $t(18)=8.31$, $p< 0.001$), while performance on intuitive trials was better than guesses (d_a: $t(18)=3.65$, $p= 0.002$), see Figure 2a & c. We did not observed higher metacognitive sensitivity when participants made rational decisions compared to intuitive decisions (ratio-intuitive meta-d_a: $t(18)=1.87$, $p= 0.078$). We did observe higher metacognitive sensitivity when participants made rational decisions compared to guesses (ratio-guess meta-d_a: $t(18)=4.55$, $p<0.001$), and intuitive decision compared to guesses (meta-d_a: $t(18)=2.71$, $p=0.014$). When we compared metacognitive efficiency (meta d_a – d_a'), we observed higher efficiency on intuitive trials than on rational trials (metacognitive efficiency: $t(18)=2.73$, $p= 0.014$). The latter result demonstrates that the increase in d' is not proportionally reflected in the increase in meta d' when participants reported to make use of a rational decision strategy. For the proportions of all ratings given a Hit, correct rejection, false alarm and miss, see Figure 2b.

To determine whether different stimulus parameters (size, color and motion) contributed differentially to first-order task accuracy and metacognitive adequacy we performed multiple linear regressions (Figure 2d). Interestingly, we observed significant positive regression coefficients for the motion, color and size indicators with respect to first-order task accuracy (all t's> 3.18, all p's <0.01), but for metacognitive adequacy we only observed significant positive regression coefficients with respect to the size indicator ($t(18)=5.66$, $p<0.01$). When we directly compared regression coefficients between first-order task accuracy and metacognitive adequacy, we observed that b values for the motion indicator were significantly lower for metacognitive adequacy ($t(18)=3.04$, $p<0.01$). These findings are in line with the answers participants provided when being explicitly asked at the end of the experiment about what kind of information they used for their decisions: Seventeen participants indicated to made use of size information, six indicated to made use of color information and six reported to made use of motion information.

Our behavioral findings indicate that presented sensory evidence differentially supports first-order task performance and second-order judgments (Charles et al., 2014; Maniscalco & Lau, 2016).

EEG results

We focused our analyses on two preselected time windows, six poolings and two frequency bands derived from data from a pilot study (Figure 3a & b). In the first second after stimulus presentation we found increased theta power in frontal ($t(18)= 3.66$, $p <0.05$, FDR-corrected) and occipital ($t(18)= 5.20$, $p <0.05$, FDR-corrected) channels compared to baseline. In this same time window we found decreased beta band activity in left and right parietal, occipital and left and right motor channels (all t's(18)> 3.59, $p <0.05$, FDR-corrected). In the late time window after stimulus presentation (1.5-2.5 s) we observed increased theta band activity in frontal channels ($t(18)= 2.90$, $p <0.05$, FDR-corrected), while we found a decrease in theta band activity in left and right motor channels ($t(18)= 3.46$ and $t(18)= 2.88$, respectively, $p <0.05$, FDR-corrected). In this later time window, we observed decreased beta band activity in frontal, left-right parietal and left-right motor channels (all t's(18)> 2.48, $p <0.05$, FDR-corrected), see Figure 3c.

In the present study, we were specifically interested in how variations in first-order task accuracy, metacognitive adequacy, and metacognitive strategy judgment are related to changes in oscillation power. We therefore performed a multiple linear regression (Cohen, 2014) to study the relationship between theta and beta power changes and diagnosis accuracy, metacognitive adequacy, and strategy judgment, while partialling out shared explained variance among the variables entered into the regression (i.e., stimulus properties, task accuracy, metacognitive adequacy, and strategy judgment; see Methods). Figures 4 and 5 show the multiple regression coefficients for the regression terms task accuracy, metacognitive adequacy, and strategy judgment. We tested whether regression coefficients differed significantly from zero for each frequency band and time window separately ($p <0.05$, FDR-corrected; significant poolings are indicated with asterisks). We observed a positive linear relationship between early ($t(18)= 3.16$, $p <0.05$, FDR-corrected) and late ($t(18)= 3.64$, $p <0.05$, FDR-corrected) prefrontal theta band activity and metacognitive adequacy, while we found a negative linear relationship between late right motor beta band activity and first-order task accuracy ($t(18)= 3.07$, $p <0.05$, FDR-corrected). These results demonstrate that theta band activity in prefrontal channels selectively relates to metacognitive adequacy. Variance in metacognitive strategy judgment was not associated significantly with oscillation power in either early or late theta or beta bands. To test whether coefficients actually differed significantly between task accuracy and metacognitive adequacy (cf. Nieuwenhuis et al., 2011), we directly compared those coefficients for prefrontal theta and found that regression coefficients were higher for metacognitive adequacy compared to first-order task accuracy in the early ($t(18)= 2.56$, $p =0.02$) and late ($t(18)= 2.69$, $p =0.03$) time window.

In the present study, we observed a relation between theta and metacognitive performance in a time window before the first-order response (i.e., the first 2.5s after stimulus onset). We constructed the task in such a way that we expected participants to have reached a first- and second-order decision before giving a first-order response. For that purpose (and for the purpose of prolonged evidence accumulation, see above), we added a jittered 1-1.5 sec time window between stimulus offset and the onset of instructions to respond. To further investigate the relationship between metacognitive performance and theta band activity, it would be interesting to examine the time window right before the second-order response. Unfortunately, we did not add a time window between first- and second-order responses. Nonetheless, we performed an additional analysis, time locking the epochs to the second-order response (using 1 second of data before the first-order response). We did not observe a significant effect ($t(18)= 1.40$, $p >0.05$, FDR-corrected). However this result should be interpreted with great caution. Indeed, because of the above described relatively long and jittered time window between stimulus offset and first-order response, the timing of stimulus onset varied per epoch when time-locking epochs to the second-order response. In dominant models of metacognition, stimulus onset is taken as the starting point of first- and second-order decisions. In future studies, it would be very interesting to investigate the relationship between theta and metacognitive performance in a distinct time window directly preceding second-order responses.

Discussion

To summarize, we applied multiple linear regression analyses to our behavioral and electrophysiological data to determine the relationship between first- and second-order performance. Results demonstrate that sources of sensory evidence contributing to first-order decision-making do not similarly support second-order decision-making. Variance in first-order diagnosis performance was driven by size, color and motion information, whereas variance in metacognitive adequacy was driven exclusively by size information. These findings suggest that part of the sensory evidence used for first-order performance becomes inaccessible or becomes susceptible to decay and noise when arriving at the stage where this sensory information is being used for metacognitive judgments (Pleskac & Busemeyer, 2010; Charles et al., 2014; Maniscalco & Lau, 2016).

To find out whether we could distinguish oscillatory mechanisms specifically related to first- and second-order task performance, we performed multiple linear regression analyses to our EEG data. We observed a positive relation between prefrontal theta band activity and metacognitive performance that could not be explained by first-order task performance or the various stimulus parameters. Further, we found that increased task accuracy related to decreased beta power in motor regions (see also Donner et al, 2007; Donner et al, 2009).

In a recent study, Maniscalso & Lau (2016) compared three dominant models that describe the relationship between objective task performance and metacognitive (subjective) task performance. In their study, they compared single channel models, which presume that the same sources of (and quality of) information support both first- and second-order task performance; dual channel models, which presume that two processing streams differentially give rise to first- and second-order task performance; and hierarchical models, which presume that a late processing stage evaluates the quality of sensory processing. Results of comparing these models demonstrated that dissociations between first- and second-order performance are best captured by hierarchical models. Maniscalso & Lau (2016) concluded that hierarchical models performed best due to the fact that such models require a less stringent relationship between the quality of information available for first- and second-order task performance.

These results and findings from the present study are in line with simulations demonstrating that a second order network is able to gradually learn to interpret contingencies related to processing in first order neural networks (Cleeremans et al., 2007). From this point of view, second-order networks could learn to evaluate the extent to which activity patterns in brain regions contributing to first-order decision-making result in successful performance.

Here, we observed that part of the information strongly supporting first order task performance (size information, see Figure 2d) also supported metacognitive performance, whereas “weaker” information (color and motion, see Figure 2d) exclusively contributed to first order task performance. These results indicate that the quality of information used for first-order performance is not similar to the quality of information used for second-order performance, possibly due to accrual of noise or signal decay (Pleskac & Busemeyer, 2010; Maniscalco & Lau, 2016). Alternatively, different sources of information can be differentially accessible for first- and second-order processes (Del Cul et al, 2009). From this perspective, size information can be seen as information processed in the “conscious” channel, whereas color and motion information are being processed in the “unconscious” channel. Although such dual channel models did not seem to most accurately capture dissociations between first- and second-order task performance in a visual backward masking task (Maniscalco & Lau, 2016), it remains to be tested whether this generalizes to other tasks or the dissociations between first- and second-order task performance we observed in the present study (Figure 2).

Information used for first- and second-order task performance

Recent work suggest that sensory evidence supporting first-order performance can become supplemented by additional sources of information that become available after a first-order decision has been made (Wierzchoń, et al., 2014; Fleming et al., 2015). For instance, it has been demonstrated that the manipulation of neural activity in premotor cortex affects metacognitive performance, without altering first-order accuracy (Fleming et al., 2015). Further, when participants had to rate the visibility of a stimulus before making a first-order decision, exhaustiveness of the scales was lower (though not for confidence judgments) in comparison with the situation in which participants provided such ratings after responding to the stimulus (Wierzchoń et al., 2014). The authors concluded that the identification task decisions affected the subsequent awareness ratings. These findings suggest that metacognition might be an “embodied” process, in which sensory evidence becomes integrated with motor and body-related information (Fleming et al., 2015; Allen et al., 2016). The availability of post-decision information that is only accessible for metacognitive processes could also contribute to the observed different relationship between presented sensory evidence and first- and second-order task performance (Figure 2d).

However, in the present study we did not observe a relationship between activity in motor channels and metacognitive adequacy, while we did observe a link between sensorimotor beta-band activity and first-order task performance. In our analyses, we focused on the time period before first-order responses, suggesting that at least motor preparatory processes do not contribute to metacognitive performance. It could be that the actual motor execution (and a possible accompanying 'sense of fluency') is necessary in order to contribute to metacognitive performance. At the present, however, this still remains to be investigated.

Here, we did observe a relationship between first-order responses and beta-band activity in motor regions, as previously reported by Donner et al. (2009). It is currently hotly debated in what way the action system is involved in decision-making (Cisek & Kalaska, 2005; Rushworth et al., 2012; Buc Calderon et al., 2016), specifically whether action selection depends on a serial or a parallel cognitive architecture. Our present findings could be interpreted as the result of continuous interactions between perceptual and action systems, which are more effective in case of correct decisions. Alternatively, the observed effect may reflect a late processing stage. Predictive activity of decision outcome might have also been evident in other regions when using more spatially refined imaging methods or recordings at the single-neuron level (Donner et al., 2009). Nonetheless, our findings demonstrate that activity related to motor preparation can be predictive of task accuracy.

Prefrontal theta oscillations

The present study indicates that metacognitive processes are orchestrated by means of prefrontal theta oscillations (Figure 4 & 5). In line with our findings, previous work demonstrated that lesions to prefrontal cortex induce metacognitive deficits, without necessarily disrupting first-order performance (Pannu & Kaszniak, 2005; Fleming et al., 2014). Similarly, modulating prefrontal cortical activity via theta burst stimulation has been shown to alter metacognitive performance, without affecting first-order decision-making (Rounis et al., 2010; Ryals et al., 2015). In the present study, we observed that specifically theta power in prefrontal channels related to metacognitive performance (Figure 4 & Figure 5).

A large body of work indicates that flexible and adaptive behavior and prefrontal theta oscillations are intimately related. It has been shown that prefrontal theta oscillations support implementation of cognitive control, action monitoring and flexible behavior (Cavanagh & Frank, 2014; Cohen, 2014; Van de Vijver, 2016). Theta band mechanisms are thought to facilitate flexible connections between prefrontal cortex and lower-tier task related networks, and allow for top-down modulation in order to adjust ongoing behavior (Cohen et al., 2009; Cohen and Cavanagh, 2011; Van Driel et al., 2015). In clinical populations, dysfunction of prefrontal theta phase dynamics has been recently linked to adaptive behavior deficits in schizophrenia (Reinhart et al., 2015). By using direct current stimulation over frontal cortex Reinhart and colleagues (2015) demonstrated that adaptive control (post-error slowing) in schizophrenia patients increased after frontal electrical stimulation. This behavioral effect coincided with a change in the organization of theta band phase dynamics. Interestingly, previous work associated schizophrenia with metacognitive deficits (Moritz & Woodward, 2002; Moritz & Woodward, 2007). Individuals with schizophrenia demonstrated impaired discriminatory capabilities between correct and incorrect judgments as reflected in confidence ratings (Moritz & Woodward, 2006). Here, the nature of the observed relationship between theta power in prefrontal channels and metacognitive performance still remains an open question. We observed the effect well before the second-order response had been made, opening the possibility that the link between metacognitive performance and prefrontal theta could be due to more general processes that support metacognition performance. Further, the way typical measures of cognitive control (e.g., post-error slowing, response conflict/inhibition [Rabbitt, 1966; Ridderinkhof et al., 2004; Charles et al., 2013; Wokke et al., 2016]) and metacognition are related (Boldt & Yeung, 2015) remains an interesting open empirical question. From this perspective, metacognition could be seen as the internalization of an initially external process, making use of similar neural mechanisms, enabling us to guide behavior more effectively (Buzsáki et al., 2014).

Fig 1. Task design

Participants made a "diagnosis" based on a pattern of moving dots that contained information indicative of illness. On each trial, participants provided judgments about the quality of their decisions and what kind of decision strategy they employed.

Fig 2. Behavioral results

a) Hit and false alarm (FA) rates for rational, intuitive decisions and guesses**. b)** Proportions of all ratings given a Hit, Miss (MS), Correct Rejection (CR) and false alarm (FA). **c)** For each decision strategy, d_a, meta-d_a and metacognitive efficiency are displayed. **d)** Regression coefficients demonstrate that different sources of information (size, color, motion) contribute differentially to first-order task performance (black bars) and metacognitive performance (grey bars). Data are means ± (between subject) SEM.

Fig 3. Time frequency analyses.

a) We used the data from a pilot study (n-=19) to pre-select our channels, frequencies and time windows of interest for statistical testing. **b)** Channels, frequencies and time windows of interest. **c)** In the first second after stimulus presentation we observed increased theta power in frontal and occipital channels. In this same time window we found decreased beta band activity in left and right parietal, occipital and left and right motor channels. In the late time window after stimulus presentation, we observed increased theta band activity in frontal channels, while we found a decrease in theta band activity in left and right motor channels. In this later time window, we observed decreased beta band activity in frontal, left-right parietal and left-right motor channels.

Fig 4. Multiple linear regression EEG results: early time window (0-1 s)

We performed a multiple linear regression to study the relationship between theta and beta power changes and diagnosis accuracy, metacognitive adequacy, and strategy judgment, while partialling out shared explained variance among the variables. **a)** We observed a positive linear relationship between prefrontal theta band activity and metacognitive adequacy. **b)** We found no effects for beta power. Asterisks indicate significant poolings.

Fig 5. Multiple linear regression EEG results: late time window (1.5-2.5 s)

a) We also observed a positive linear relationship between prefrontal theta band activity and metacognitive adequacy in the late time window. **b)** In this time window we also observed a negative linear relationship between late right motor beta band activity and first-order task accuracy. Asterisks indicate significant poolings.

References

Allen, M., Fardo, F., Dietz, M. J., Hillebrandt, H., Friston, K. J., Rees, G., & Roepstorff, A. (2016). Anterior insula coordinates hierarchical processing of tactile mismatch responses. *NeuroImage*, *127*, 34-43.

Baranski, J. V., & Petrusic, W. M. (1998). Probing the locus of confidence judgments: experiments on the time to determine confidence. *Journal of Experimental Psychology: Human Perception and Performance*, *24*(3), 929.

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, 289-300.

Berry, D., & Dienes, Z. P. (1993). *Implicit learning: Theoretical and empirical issues*. Psychology Press.

Boldt, A., & Yeung, N. (2015). Shared neural markers of decision confidence and error detection. *The Journal of Neuroscience*, *35*(8), 3478-3484.

Buzsáki, G., Peyrache, A., & Kubie, J. (2014). Emergence of cognition from action. *In Cold Spring Harbor symposia on quantitative biology* (Vol. 79, pp. 41-50). Cold Spring Harbor Laboratory Press.

Calderon, C. B., Verguts, T., & Gevers, W. (2015). Losing the boundary: Cognition biases action well after action selection. *Journal of Experimental Psychology: General*, 144(4), 737.

Cavanagh, J. F., & Frank, M. J. (2014). Frontal theta as a mechanism for cognitive control. *Trends in cognitive sciences*, *18*(8), 414-421.

Charles, L., King, J. R., & Dehaene, S. (2014). Decoding the dynamics of action, intention, and error detection for conscious and subliminal stimuli. *The journal of Neuroscience*, *34*(4), 1158-1170.

Charles, L., Van Opstal, F., Marti, S., & Dehaene, S. (2013). Distinct brain mechanisms for conscious versus subliminal error detection. *Neuroimage*,*73*, 80-94.

Cisek, P., & Kalaska, J. F. (2005). Neural correlates of reaching decisions in dorsal premotor cortex: specification of multiple direction choices and final selection of action. *Neuron*, 45(5), 801-814.

Cleeremans, A., Destrebecqz, A., & Boyer, M. (1998). Implicit learning: News from the front. *Trends in cognitive sciences*, 2(10), 406-416.

Cleeremans, A., Timmermans, B., & Pasquali, A. (2007). Consciousness and metarepresentation: A computational sketch. *Neural Networks*, *20*(9), 1032-1039.

Cohen, M. X., & Cavanagh, J. F. (2011). Single-trial regression elucidates the role of prefrontal theta oscillations in response conflict. *Frontiers in psychology*, *2*, 30.

Cohen, M. X. (2014). *Analyzing neural time series data: theory and practice*. MIT Press.

Cohen, M. X., Van Gaal, S., Ridderinkhof, K. R., & Lamme, V. (2009). Unconscious errors enhance prefrontal-occipital oscillatory synchrony.*Frontiers in human neuroscience*, *3*, 54.

Del Cul, A., Dehaene, S., Reyes, P., Bravo, E., & Slachevsky, A. (2009). Causal role of prefrontal cortex in the threshold for access to consciousness.*Brain*, *132*(9), 2531-2540.

Desender, K., Van Opstal, F., Hughes, G., & Van den Bussche, E. (2016). The temporal dynamics of metacognition: Dissociating task-related activity from later metacognitive processes. *Neuropsychologia*.

Donner, T. H., & Siegel, M. (2011). A framework for local cortical oscillation patterns. *Trends in cognitive sciences*, *15*(5), 191-199.

Donner, T. H., Siegel, M., Oostenveld, R., Fries, P., Bauer, M., & Engel, A. K. (2007). Population activity in the human dorsal pathway predicts the accuracy of visual motion detection. *Journal of Neurophysiology*, *98*(1), 345-359.

Donner, T. H., Siegel, M., Oostenveld, R., Fries, P., Bauer, M., & Engel, A. K. (2007). Population activity in the human dorsal pathway predicts the accuracy of visual motion detection. *Journal of Neurophysiology*, 98(1), 345-359.

Donner, T. H., Siegel, M., Fries, P., & Engel, A. K. (2009). Buildup of choice-predictive activity in human motor cortex during perceptual decision making. *Current Biology*, *19*(18), 1581-1585.

Engel, A. K., & Fries, P. (2010). Beta-band oscillations—signalling the status quo?. *Current opinion in neurobiology*, *20*(2), 156-165.

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

Fleming, S. M., & Dolan, R. J. (2012). The neural basis of metacognitive ability. *Phil. Trans. R. Soc. B*, *367*(1594), 1338-1349.

Fleming, S. M., & Lau, H. C. (2014). How to measure metacognition. *Frontiers in human neuroscience*, *8*(July), 1-9.

Fleming, S. M., Maniscalco, B., Ko, Y., Amendi, N., Ro, T., & Lau, H. (2015). Action-specific disruption of perceptual confidence. *Psychological science*,*26*(1), 89-98.

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.

Haegens, S., Nácher, V., Hernández, A., Luna, R., Jensen, O., & Romo, R. (2011). Beta oscillations in the monkey sensorimotor network reflect somatosensory decision making. *Proceedings of the National Academy of Sciences*, *108*(26), 10708-10713.

Harsay, H. A., Spaan, M., Wijnen, J. G., & Ridderinkhof, K. R. (2012). Error awareness and salience processing in the oddball task: shared neural mechanisms. *Front Hum Neurosci*, *6*, 246.

Hebart, M. N., Schriever, Y., Donner, T. H., & Haynes, J. D. (2014). The relationship between perceptual decision variables and confidence in the human brain. *Cerebral Cortex*, bhu181.

Kalcher, J., & Pfurtscheller, G. (1995). Discrimination between phase-locked and non-phase-locked event-related EEG activity. *Electroencephalography and clinical neurophysiology*, *94*(5), 381-384.

Kiani, R., Corthell, L., & Shadlen, M. N. (2014). Choice certainty is informed by both evidence and decision time. *Neuron*, *84*(6), 1329-1342.

Kiani, R., & Shadlen, M. N. (2009). Representation of confidence associated with a decision by neurons in the parietal cortex. *science*, *324*(5928), 759-764.

King, J. R., & Dehaene, S. (2014). A model of subjective report and objective discrimination as categorical decisions in a vast representational space.*Philosophical Transactions of the Royal Society of London B: Biological Sciences*, *369*(1641), 20130204.

Kloosterman, N. A. (2015). *Brain state and changes of mind: Probing the neural bases of multi-stable perceptual dynamics*.

Kloosterman, N. A., Meindertsma, T., Hillebrand, A., van Dijk, B. W., Lamme, V. A., & Donner, T. H. (2015). Top-down modulation in human visual cortex predicts the stability of a perceptual illusion. *Journal of neurophysiology*,*113*(4), 1063-1076.

Macmillan, N. A., & Creelman, C. D. (2004). Detection theory: A user's guide. Psychology press.

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

Maniscalco, B., & Lau, H. (2016). The signal processing architecture underlying subjective reports of sensory awareness. *Neuroscience of Consciousness*, *2016*(1), niw002.

Mitra, P. P., & Pesaran, B. (1999). Analysis of dynamic brain imaging data.*Biophysical journal*, *76*(2), 691-708.

Moritz, S., & Woodward, T. S. (2002). Memory confidence and false memories in schizophrenia. *The Journal of nervous and mental disease*,*190*(9), 641-643.

Moritz, S., Woodward, T. S., & Rodriguez-Raecke, R. (2006). Patients with schizophrenia do not produce more false memories than controls but are more confident in them. *Psychological medicine*, *36*(05), 659-667.

Moritz, S., & Woodward, T. S. (2007). Metacognitive training in schizophrenia: from basic research to knowledge translation and intervention. *Current Opinion in Psychiatry*, *20*(6), 619-625.

Nieuwenhuis, S., Forstmann, B. U., & Wagenmakers, E. J. (2011). Erroneous analyses of interactions in neuroscience: a problem of significance. *Nature neuroscience*, *14*(9), 1105-1107.

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J. M. (2010). FieldTrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational intelligence and neuroscience*,*2011*.

Pannu, J. K., & Kaszniak, A. W. (2005). Metamemory experiments in neurological populations: A review. *Neuropsychology review*, *15*(3), 105-130.

Pleskac, T. J., & Busemeyer, J. R. (2010). Two-stage dynamic signal detection: a theory of choice, decision time, and confidence. *Psychological review*, *117*(3), 864.

Price, M. C., & Norman, E. (2008). Intuitive decisions on the fringes of consciousness: Are they conscious and does it matter? *Judgment and Decision Making*, 3(1), 28.

Siegel, M., Donner, T. H., & Engel, A. K. (2012). Spectral fingerprints of large-scale neuronal interactions. *Nature Reviews Neuroscience*, *13*(2), 121-134.

Rabbitt, P. M. (1966). Errors and error correction in choice-response tasks. *Journal of experimental psychology*, *71*(2), 264.

Reinhart, R. M., Zhu, J., Park, S., & Woodman, G. F. (2015). Medial–Frontal Stimulation Enhances Learning in Schizophrenia by Restoring Prediction Error Signaling. *The Journal of Neuroscience*, *35*(35), 12232-12240.

Ridderinkhof, K. R., Ullsperger, M., Crone, E. A., & Nieuwenhuis, S. (2004). The role of the medial frontal cortex in cognitive control. *science*, *306*(5695), 443-447.

Rounis, E., Maniscalco, B., Rothwell, J. C., Passingham, R. E., & Lau, H. (2010). Theta-burst transcranial magnetic stimulation to the prefrontal cortex impairs metacognitive visual awareness. *Cognitive Neuroscience*, *1*(3), 165-175.

Rousselet, G. A., Husk, J. S., Pernet, C. R., Gaspar, C. M., Bennett, P. J., & Sekuler, A. B. (2009). Age-related delay in information accrual for faces: evidence from a parametric, single-trial EEG approach. *BMC neuroscience*,*10*(1), 1.

Rushworth, M. F., Kolling, N., Sallet, J., & Mars, R. B. (2012). Valuation and decision-making in frontal cortex: one or many serial or parallel systems?. *Current opinion in neurobiology*, 22(6), 946-955.

Ryals, A. J., Rogers, L. M., Gross, E. Z., Polnaszek, K. L., & Voss, J. L. (2015). Associative recognition memory awareness improved by theta-burst stimulation of frontopolar cortex. *Cerebral Cortex*, bhu311.

Steinhauser, M., & Yeung, N. (2010). Decision processes in human performance monitoring. *The Journal of neuroscience*, *30*(46), 15643-15653.

van Driel, J., Swart, J. C., Egner, T., Ridderinkhof, K. R., & Cohen, M. X. (2015). (No) time for control: Frontal theta dynamics reveal the cost of temporally guided conflict anticipation. *Cognitive, Affective, & Behavioral Neuroscience*, *15*(4), 787-807.

Van Vugt, M. K., Simen, P., Nystrom, L. E., Holmes, P., & Cohen, J. D. (2014). EEG oscillations reveal neural correlates of evidence accumulation.*Dynamics of decision making: from evidence to preference and belief*, 108.

Vigário, R. N. (1997). Extraction of ocular artefacts from EEG using independent component analysis. *Electroencephalography and clinical neurophysiology*, *103*(3), 395-404.

Vijver, I. (2016). Functional and structural connectivity underlying reinforcement learning in young and older adults.

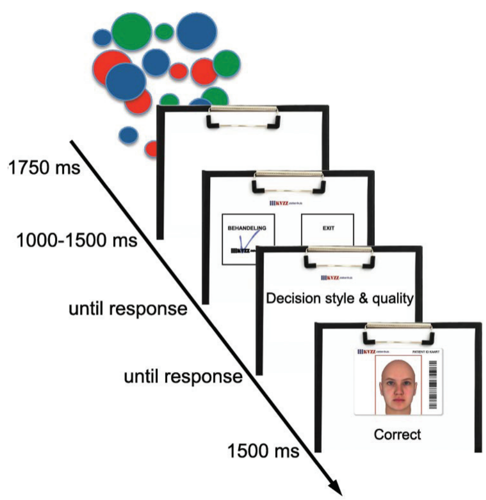
Weiskrantz, L., Warrington, E. K., Sanders, M. D., & Marshall, J. (1974). Visual capacity in the hemianopic field following a restricted occipital ablation.*Brain*, *97*(1), 709-728.

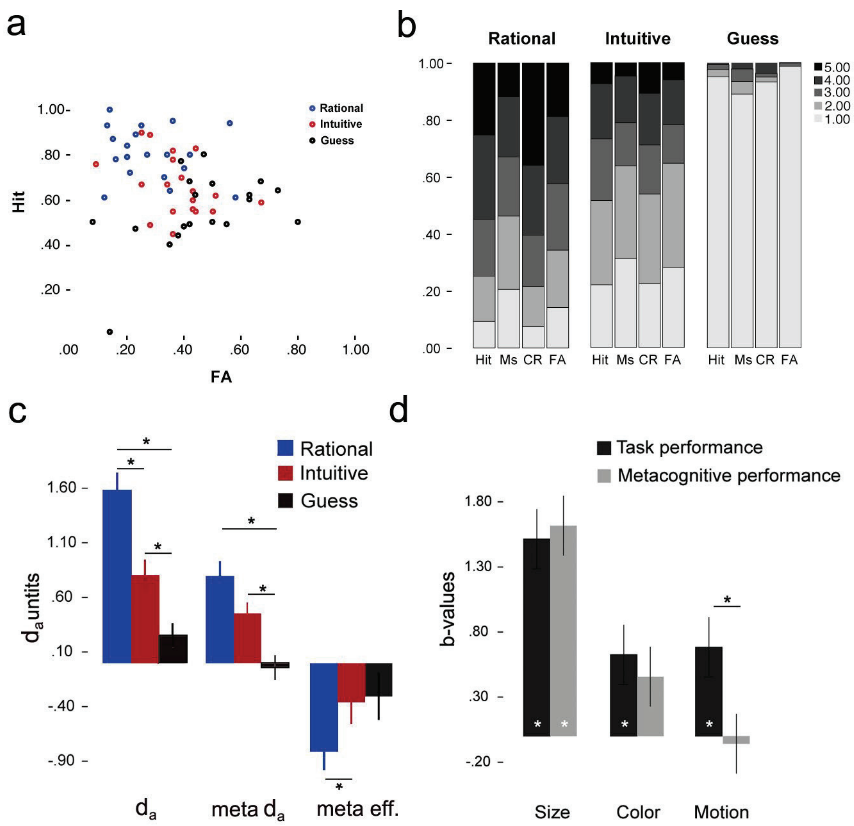
Werkle-Bergner, M., Grandy, T. H., Chicherio, C., Schmiedek, F., Lövdén, M., & Lindenberger, U. (2014). Coordinated within-trial dynamics of low-frequency neural rhythms controls evidence accumulation. *The Journal of Neuroscience*, *34*(25), 8519-8528.

Wierzchoń, M., Paulewicz, B., Asanowicz, D., Timmermans, B., & Cleeremans, A. (2014). Different subjective awareness measures demonstrate the influence of visual identification on perceptual awareness ratings. *Consciousness and cognition*, *27*, 109-120.

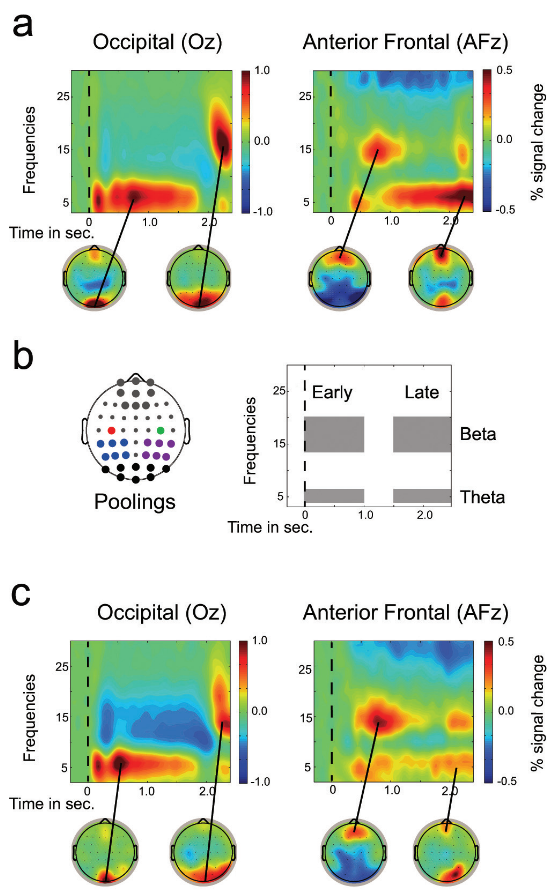
Wokke, M. E., Knot, S. L., Fouad, A., & Ridderinkhof, K. R. (2016). Conflict in the kitchen: Contextual modulation of responsiveness to affordances. *Consciousness and cognition*, *40*, 141-146.

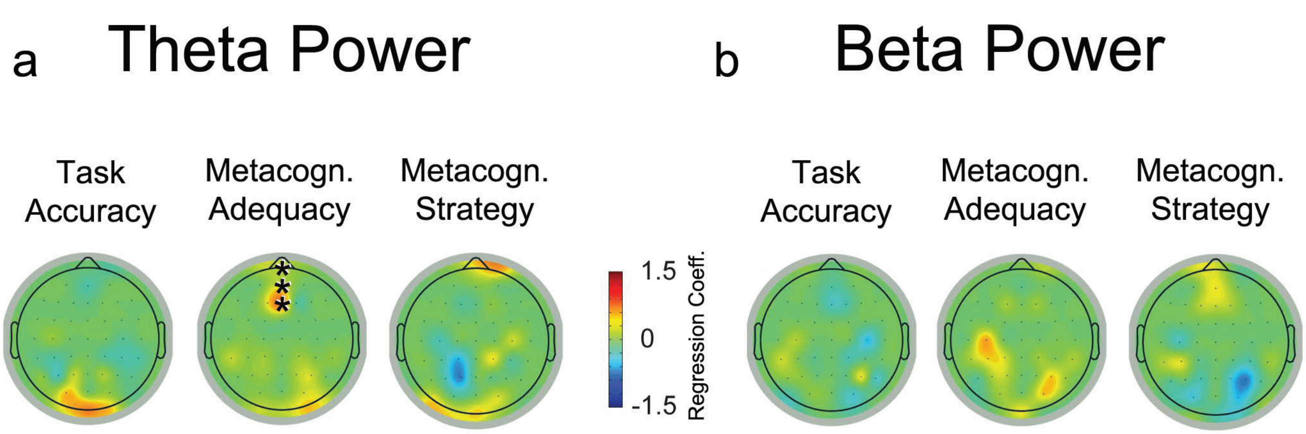
Yeung, N., & Summerfield, C. (2012). Metacognition in human decision-making: confidence and error monitoring. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, *367*(1594), 1310-1321.

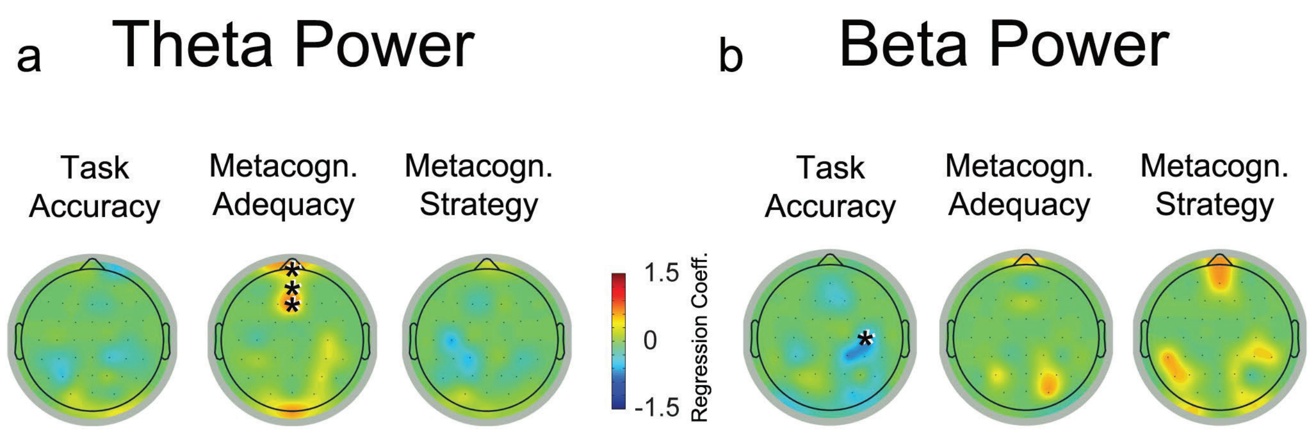

1750 ms
1000-1500 ms
until response
until response
1500 ms
BEHANDELING
EXIT
Decision style & quality
Correct



a
Rational
Intuitive
Guess
Hit
FA
b
Rational
Intuitive
Guess
5.00
4.00
3.00
2.00
1.00
Hit Ms CR FA
c
Rational
Intuitive
Guess
d_a untits
d_a
meta d_a
meta eff.
d
Task performance
Metacognitive performance
b-values
Size
Color
Motion


a
Occipital (Oz)
Anterior Frontal (AFz)
Frequencies
Time in sec.
% signal change
b
Poolings
Early
Late
Beta
Theta
c
Occipital (Oz)
Anterior Frontal (AFz)


a
Theta Power
b
Beta Power
Task Accuracy
Metacogn. Adequacy
Metacogn. Strategy
Task Accuracy
Metacogn. Adequacy
Metacogn. Strategy
1.5
0
-1.5
Regression Coeff.


a
Theta Power
b
Beta Power
Task Accuracy
Metacogn. Adequacy
Metacogn. Strategy
Task Accuracy
Metacogn. Adequacy
Metacogn. Strategy
1.5
0
-1.5
Regression Coeff.