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RESEARCH ARTICLE

# A magnetoencephalography study of choice bias

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**Abstract** Many factors can influence, or bias, human decision making. A considerable amount of research has investigated the neural correlates of such biases, mostly correlating hemodynamic responses in brain areas with some aspect of the decision. These studies, typically done using functional magnetic resonance imaging or positron emission tomography, have provided useful information about the location of processing in the brain. However, comparatively little research has examined when these processes occur. The present experiment addressed this question by using magnetoencephalography (MEG) to record brain activity while subjects chose preferred options from decision sets. We found that MEG signal deviations for biased decisions occurred as early as 250–750 ms following stimulus onset. Such deviations occurred earliest in sensors over the right anterior cortex. These findings improve our understanding of temporal dynamics of decision biases and suggest ways that existing explanations for this bias could be refined.

**Keywords** Neuroeconomics · Decision neuroscience · Magnetoencephalography · Preferences · Choice · Decoy

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## Introduction

Neuroeconomics combines neuroscientific techniques with economic theories to investigate the neural correlates of economic decision making. Many categories of decisions have been studied, including decision making with probabilistic outcomes (Dickhaut et al. 2003; Shiv et al. 2005), positive and negative framing (De Martino et al. 2006), intertemporal choice (McClure et al. 2004a), brand names (McClure et al. 2004b), and the effect of irrelevant alternatives on choice (Hedgcock and Rao 2009). These studies have made significant contributions to our understanding of decision biases by locating areas of processing differences but comparatively little research has been done to investigate when these differences occur.

Temporal characteristics of neurological function have been documented in many other aspects of cognition. These aspects of research have benefited from the use of techniques with high temporal resolution, including electroencephalography or magnetoencephalography (MEG). However, such studies of decision making are relatively more rare, although topics such as temporal discounting (Delaney et al. 2008), cooperative games (Yun et al. 2008) and choices with probabilistic outcomes (Gehring and Willoughby 2002; Hewig et al. 2006; Polezzi et al. 2008; Schutter et al. 2004) have recently received attention.

**Table 1** Example of relative attribute values

| Alternative | Crime rate | Cost | Description |
|---|---|---|---|
| Non-target | 7 per 1,000 | $700 | Best crime rate/worst cost |
| Target | 15 per 1,000 | $620 | Best cost/worst crime rate |
| Decoy | 15 per 1,000 | $634 | Moderate cost/worst crime rate |

The first option (non-target) has the best option for crime rate but worst for cost. The second option (target) has the best cost but worst crime rate. The third option (decoy) is more expensive than the second option, but also has the worst crime rate. The decoy should never be chosen as it is inferior to the target

The present study addressed this gap in the research. Specifically, we used MEG to study neural activity while human subjects made decisions in the presence of a decoy option. For example, one choice set included three apartment options described with two attributes: crime rate and cost (Table 1). One option had the best (lowest) crime rate, whereas the second option had the lowest cost. The third option had the same crime rate as the second option, but a higher cost. This third option, namely the decoy (Fig. 1a), should be irrelevant to the decision as it is inferior to the second option. However, Huber et al. (1982) found that these decoys shift choices towards the similar but superior option (Table 1, "Target"). This preference shift (the "decoy effect") has been replicated in several studies (Dhar and Simonson 2003; Huber and Puto 1983; Luce 1998; Pettibone and Wedell 2000; Simonson 1989; Wedell and Pettibone 1996). Although the decoy effect has been well documented, researchers still do not agree why the bias occurs. Here, we show that processing differences occur within 1 s of stimulus onset, providing support for theories that predict that differences should occur early in the decision process.

## Materials and methods

### Subjects

Nine healthy right-handed human subjects participated in the MEG study as paid volunteers (7 men and 2 women; mean age ± SEM = 29.3 ± 2.4 y). The study protocol was approved by the appropriate institutional review boards and informed consent was obtained from all subjects before the study, according to the Declaration of Helsinki.

### Task

The choice task was presented sequentially over four screens (Fig. 2), as follows. (i) The first screen described the choice problem and automatically advanced after 14 s; (ii) the second screen had a fixation cross "+" in the middle which was presented for 2 s; (iii) the third screen displayed information for three options described with two attributes. Subjects had up to 14 s to select a preferred option by pressing "1", "2", or "3" on a number pad that was placed under their right hand; finally, (iv) after the 14 s had expired, subjects saw a fixation cross "+" again for 2 s (fourth screen). This 4-screen sequence was repeated for subsequent trials. Subjects answered a total of 42 questions (trials) during the experiment, divided into 2 blocks of 21 questions each. In two-thirds of the trials, a decoy option was included; the decoy option was absent in one-third of the trials ("na" option, Fig. 1b).

Subjects were instructed to choose their preferred option. In addition, they were told that there were no right or wrong decisions, except that they should not choose options described with attributes of "na" (Fig. 1b). The MEG environment required some additional instructions. Specifically, subjects were told they should fixate on the middle of the screen and not blink during the choice portion of the experiment. Subjects then practiced the choice task with two practice questions. After practice, subjects had an opportunity to ask for clarification.

All subjects answered the same set of questions; the order of questions within blocks was randomized between subjects.

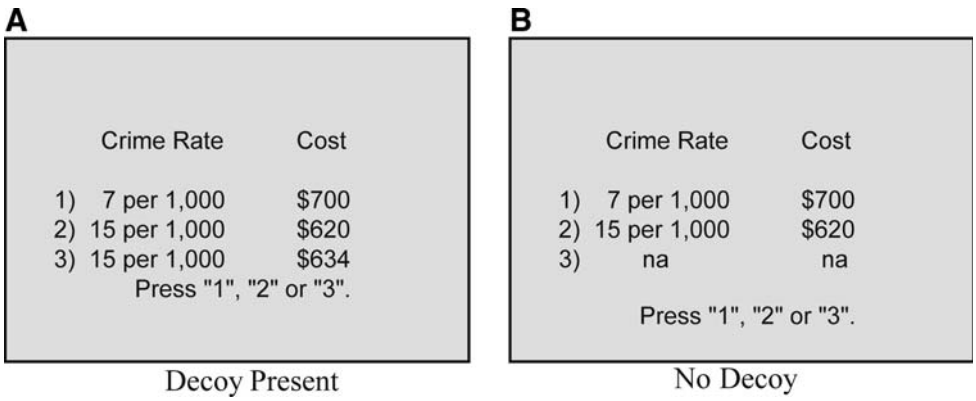


**Fig. 1** Example of the No Decoy and Decoy Present stimuli

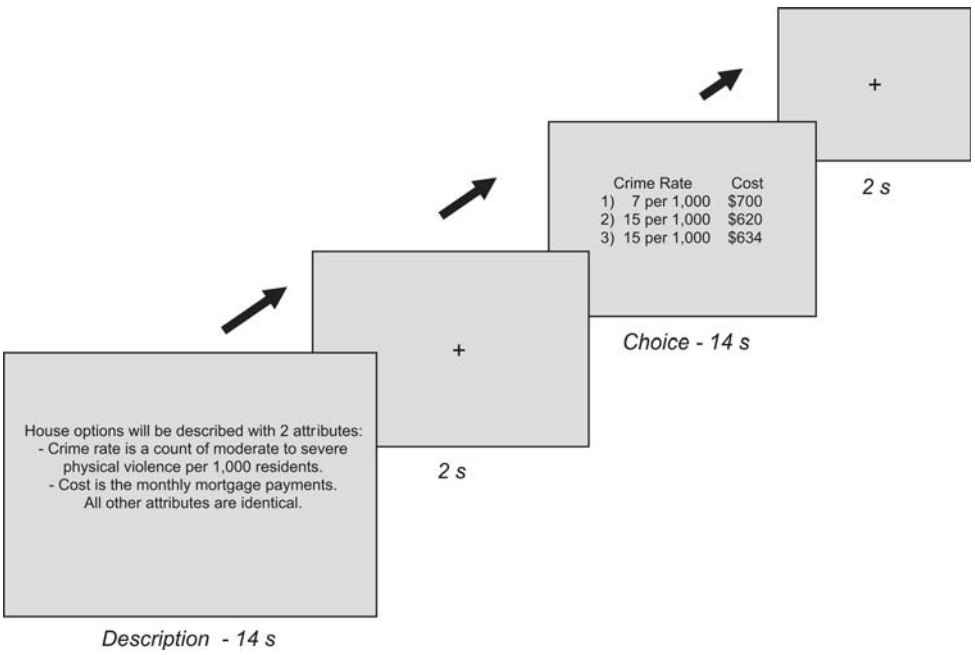


**Fig. 2** Task description. One trial is shown. Subjects viewed a screen with the choice problem for 14 s. After a two-second fixation screen, the subjects were then presented with either two or three options, each described with two attributes. This screen was visible for 14 s. Subjects were instructed to maintain fixation as best as possible during this screen and to refrain from blinking. They pressed one of three buttons to indicate their choice. The last screen was another two-second fixation screen, which was followed by the choice problem screen of the next trial. Each subject performed 42 trials

## MEG recording

Subjects performed the decoy task while MEG data were acquired from a 248-channel axial gradiometer MEG system (Magnes 3600 WH, 4D-Neuroimaging, San Diego, CA, USA), which was located within an electromagnetically shielded room to reduce environmental noise. MEG data were acquired at 1,017.25 Hz and low-pass filtered at 400 Hz prior to digitization. The state of three buttons was sampled at the same rate as the MEG data (at 1,017.25 Hz) and was incorporated directly into the MEG data file to ensure correct time alignment. Cardiac artifact was removed after recording by the method of event synchronous subtraction (Storbach et al. 1994; Leuthold 2003). Next, MEG signals were noise-reduced using the 4D Magnes noise reduction algorithms, a procedure that takes into account and removes environmental noise recorded by separate (reference) channels. In addition, all data were free from obvious artifacts. Finally, the data were high-pass filtered using a 0.1 Hz cutoff.

## MEG analysis

To find sensors whose activity in time differed between trials in which subjects either chose targets options or non-targets (Table 1), we applied a sequential test, using an open plan with known variability (Armitage 1975). For this test, two MEG time courses (10 ms bins) were compared for each sensor, namely the average time course across all subjects for target choices, and the average time course across all subjects for non-target choices. Each averaged time course was normalized to baseline by subtracting the mean value for the first 100 ms. At each time point, a difference between target and non-target choice time courses was calculated. The cumulative sum (CUSUM) of these differences was then compared to an upper and a lower bound. These bounds were defined by a constant and a slope, which are empirically defined coefficients (Armitage 1975, p. 98). Specifically, the upper boundary was defined as a line given by the following equation,

$$y = a\sigma + b\sigma n \quad (1)$$

and the lower boundary was defined by

$$y = -a\sigma - b\sigma n \quad (2)$$

where $a$ and $b$ are the empirically defined coefficients, $\sigma$ is the standard deviation of the differences between the two time courses across the entire trial, and $n$ is the number of time bins. The coefficients $a$ and $b$ were chosen to give an approximate two-sided overall significance level of $\alpha \approx 0.05$, and a power of $(1 - \beta) \approx 0.95$ at a critical value of $\mu/\sigma = 1.6$, where $\mu$ is the mean of the distribution of the sums of differences between MEG time courses (Armitage 1975, Table 5.1).

This resulted in two lines, symmetrical about the $x$-axis, which diverged with time (Fig. 3) to take into account the repeated testing procedure. If the magnitude of the CUSUM of the time course differences exceeded either bound, the sensor was labeled as "significant". The onset time of a significant divergence was the first time bin in the trial in which the magnitude of the CUSUM of the differences exceeded one of the bounds. This analysis was repeated to identify sensors the activity of which differed significantly between trials in which subjects chose between decision sets that included a decoy and those in which no decoy was present.

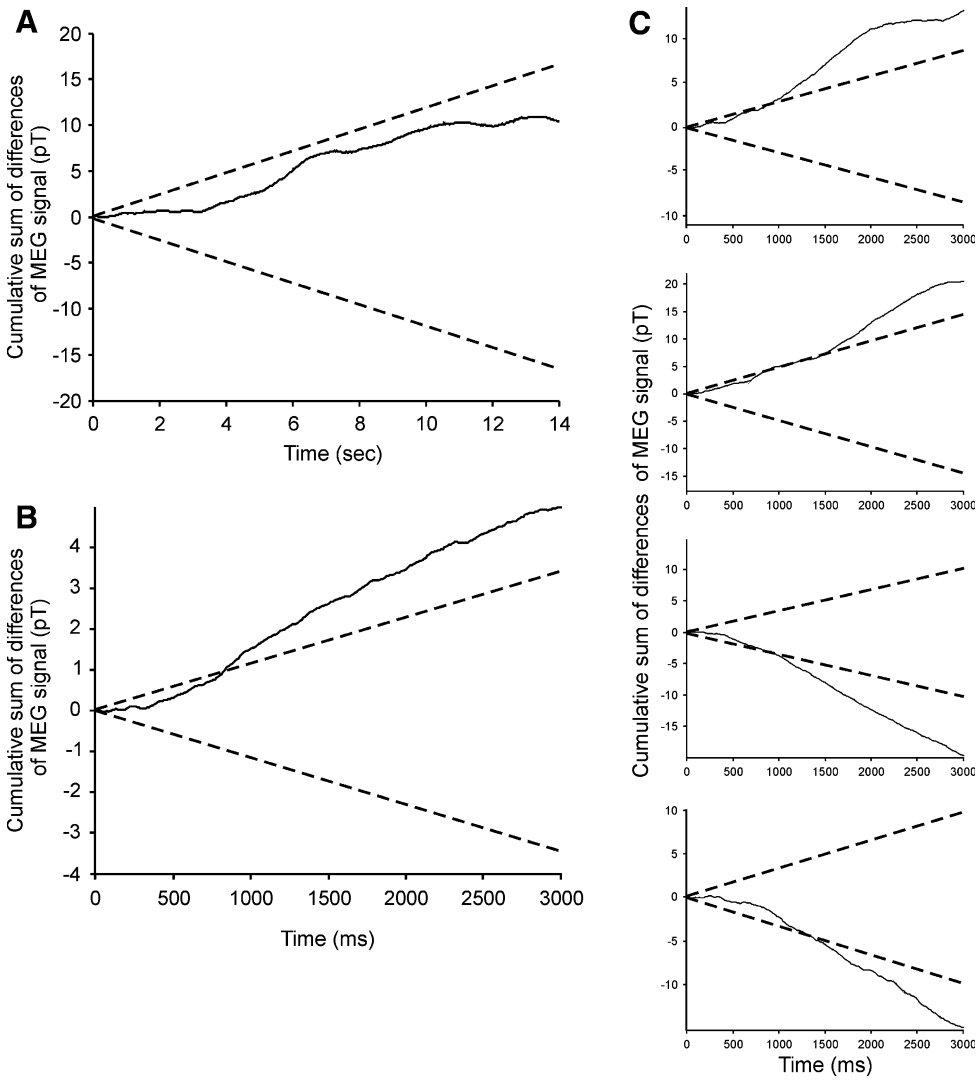


**Fig. 3** Sequential trials test applied to MEG signals. The significance boundaries diverge to account for the multiple comparisons (every 10 ms) (Armitage 1975). **a** *Solid line* is the CUSUM of the differences between MEG signals (averaged across subjects) on target-chosen and non-target-chosen trials. The *dotted lines* indicate boundaries of significance. In this case, the differences between signals was not significant. **b** *Lines* as in **a**. In this case, the difference in signals became significant at about 900 ms. (Note the different *x*-axis scale.) **c** Examples from individual subjects

To determine how the time course of MEG activity was related to response times in the task, we repeated the time course analysis above on a trial-by-trial basis. Since this analysis assessed differences between trials, we first paired MEG time courses from each decoy trial in which the target option was chosen with every other decoy trial in which the non-target option was chosen. We then performed the time course analysis above on all possible pairs, noting the time that the MEG signals significantly differed.

## Results

### Differences in MEG signal in decoy trials, depending on subject choice

We used a sequential analysis (Armitage 1975) on data restricted to cases with a decoy option, looking for differences in MEG signals between trials when subjects chose the target option and trials when they did not. In this test, we compared the CUSUM of the differences between the average time courses of MEG activity on these two types of trials. Sensors were deemed to have significantly different time courses if this CUSUM exceeded a statistically defined threshold (Fig. 3a–c). Overall, 167 sensors (67%) showed a significant difference between target-chosen and non-target-chosen conditions. Different shapes in Fig. 4 indicate the location of each significant sensor and the time at which each sensor showed a significant difference. It can be seen that many sensors showed differential activity early. Sensors located above the right anterior hemisphere, as well as those near the midline showed significant differences in activity within 1,000 ms of the display of the choices, depending on whether subjects chose the target option or the non-target option. To investigate the timing relationship between neural signal and response time, we applied the sequential analysis above on all possible target-chosen/non-target-chosen trial

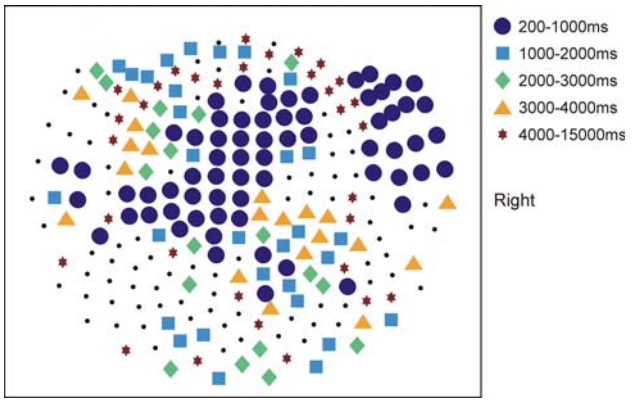


**Fig. 4** Location and times of significance of sensors, comparing target and non-target choices on decoy trials. *Symbols* indicate sensors with significant results in the sequential trials test

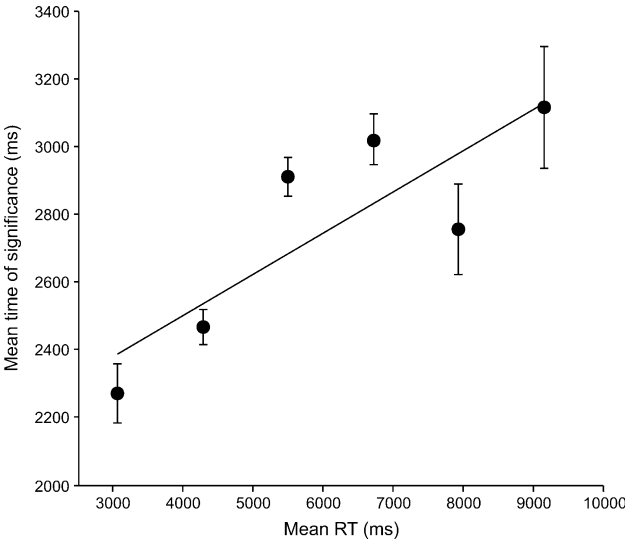


**Fig. 5** Relationship between response time and divergence of neural signals between target- and non-target-chosen decoy trials. *Dots and error bars* indicate the mean time of significance for MEG signals in decoy trials (± 2 SEM)

pairs. Comparing the time of divergence of the MEG signal to the mean response time of the two trials in the pair, we found that in 84% of the cases across all sensors, the divergence preceded the average response time (mean 3,249 ms). This result was consistent for each of the sensors, taken individually. All sensors showed a majority of cases in which the change in neural signal preceded the mean response times (range 74–92%). Interestingly, there was a small but significant positive correlation between the time of MEG signal divergence and mean response time in these pairs of trials ($r = 0.04$, $p < 0.001$). To look at the central tendency of this noisy signal, we averaged times of neural activity divergence across bins of response time. These results are shown in Fig. 5.

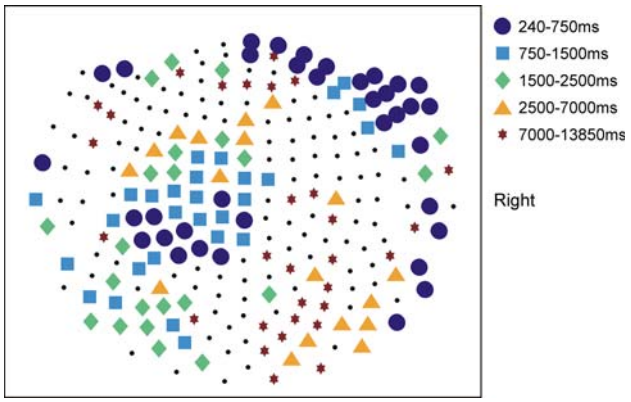


**Fig. 6** Location and times of significance of sensors, comparing decoy present and no decoy trials. *Symbols* indicate sensors with significant results in the sequential trials test

## MEG signal differences between decoy and non-decoy trials

We performed the above time course analysis on the complete set of data to determine which sensors' activity differed between trials which included a decoy option ("decoy present") and those that did not ("no decoy" trials). Of the 248 sensors, 135 (54%) showed a significant difference between decoy present and no decoy trials. Sensors in the right, anterior area showed significant effects within the first 750 ms (Fig. 6).

Interestingly, the MEG signal divergence between decoy present and no decoy trials preceded the mean RT in every subject (Table 2). To investigate the timing relationship between neural signal and response time, we performed the sequential analysis above on all possible decoy present/no decoy trial pairs. MEG signal divergence in these cases tended to precede the response time in a manner similar to

**Table 2** Reaction time and MEG signal divergence between decoy and no decoy trials

| Subject | Mean RT (ms) | Mean time of MEG signal divergence (ms) |
|---|---|---|
| 1 | 6,009 ± 327 | 4,010 ± 2, $N = 25{,}829$ |
| 2 | 7,707 ± 446 | 3,738 ± 2, $N = 25{,}195$ |
| 3 | 6,234 ± 238 | 3,854 ± 2, $N = 26{,}383$ |
| 4 | 4,431 ± 198 | 3,327 ± 2, $N = 21{,}722$ |
| 5 | 7,229 ± 432 | 3,849 ± 2, $N = 23{,}230$ |
| 6 | 7,514 ± 310 | 1,321 ± 1, $N = 18{,}476$ |
| 7 | 6,638 ± 292 | 1,803 ± 1, $N = 18{,}004$ |
| 8 | 3,494 ± 226 | 1,316 ± 1, $N = 18{,}550$ |
| 9 | 6,885 ± 305 | 1,374 ± 1, $N = 17{,}072$ |

Data are means ± standard error. For mean response times, $N = 42$ trials. For mean time of MEG signal divergence, $N =$ the indicated number of significant trial pairs

that described above. We found that in 83% of the cases, the signal divergence preceded the average response time of a pair of trials. This was the case for all sensors, taken individually (range 73–90%). Over all pairs and sensors, the mean difference in these measures was 3,050 ms (i.e., on average, the MEG signal preceded the mean response time by about 3 s). When comparing the divergence of neural signal to the minimum of the two response times in each pair, we found that the signal divergence preceded the minimum response time in 78% of cases. Similar results were found for when all sensors were taken individually (range 66–86%). Over all pairs and sensors, the overall mean difference between the minimum of the response times in the pair and the time of MEG signal divergence was 1,893 ms.

## Discussion

This study used MEG to collect brain activation data with high temporal resolution to demonstrate when the presence of decoy options changes decision processing. Right frontal areas of the brain showed neural activity differences within 750 ms when subjects considered choice sets with a decoy versus choice sets without a decoy. These same areas of the brain had activity differences within 1,000 ms when we compared choices of the target or non-target. These results suggest that decoys affect neural processing considerably before the decision is made and that these differences may ultimately result in biased decisions.

We also found that MEG signal divergence between decoy and non-decoy trials occurred an average of 3 s before the decision. It is interesting to consider what may be occurring during the time between divergence and the decision. Soon et al. (2008) have recently demonstrated that activity in the brain can predict decisions up to ten seconds before they enter the subject's conscious awareness. They suggest, "[h]igh-level control areas can begin to shape an upcoming decision long before it enters awareness," (Soon et al. 2008, p. 545). Prior research indicates subjects are unaware that decoys affect their choices (Dhar and Simonson 2003). Taken together, we suggest it is possible that the decoy begins to bias information processing even before the decision is made and that this bias could be outside of the subject's awareness.

It is interesting then to consider what the nature of these early cognitive differences might be. Anterior sensors in our analyses are sensitive to processing differences in frontal brain areas, such as the dorsolateral prefrontal cortex (DLPFC). Activity in the DLPFC has been correlated with increased working memory demands. This might suggest that sensor differences in the decoy present versus no decoy tasks are related to differences in working memory. However, this explanation cannot explain why the same sensors have differences when the analysis is limited to trials where a decoy was present and the only difference was the subject's choice of the target or non-target. Recent research has implicated the DLPFC in rules-based decision processes (Huettel and Misiurek 2004). Early differences in rules-based processing would be consistent with a heuristic based on dominance. In some instances, it can be appropriate to use neural activity differences to infer that two tasks have different cognitive processing demands (Poldrack 2006). However, our use of MEG makes these inferences inappropriate. MEG has worse spatial localization than other brain imaging methods like functional magnetic resonance imaging and positron emission tomography. This limited spatial capability makes it impossible to make any specific claims about which structures had processing differences. Therefore, this rules-based explanation should be considered highly speculative though it may be a fruitful direction for further research.

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