A role for retro-splenial cortex in the task-related P3 network

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Abstract

The P3 is an event-related response observed in relation to task-relevant sensory events. Despite its ubiquitous presence, the generators of the P3 are controversial and not well identified. Here, we compared source analysis of combined magneto- and electro–encephalography (MEG and EEG) data with fMRI and simulation studies to better understand the sources of the P3 in an auditory oddball paradigm. Our results suggest that the dominant source of the classical, postero-central P3 lies in the retro-splenial cortex of the ventral cingulate gyrus. A second P3 source in the anterior insular cortex contributes little to the postero-central maximum. Multiple other sources in the auditory, somatosensory, and anterior middle cingulate cortex are active in an overlapping time window but can be functionally dissociated based on their activation time courses. These results provide a new perspective for the interpretation of the extensive research based on the P3 response.

Keywords: P300, retro-splenial cortex, insular cortex, EEG, MEG, fMRI, source analysis

Introduction

Many tasks that we perform in response to sensory events recruit widespread cortical networks [Hugdahl et al., 2015; Kim, 2014] as detected by functional magnetic resonance imaging (fMRI). In electroencephalography (EEG), such task-relevant stimuli ubiquitously evoke the prominent P3 [Sutton et al., 1965], also called P300, which has been explored by a large number of cognitive neuroscience studies including such diverse fields as consciousness [Sergent et al., 2005], mental disorders [Hamilton et al., 2020], or brain-computer interfaces [Chaudhary et al., 2016]. Two variants of the P3 have been studied: the earlier P3a is evoked by rare, salient events which are not assigned as target in an active task; it is recorded over more anterior sites in EEG. The later P3b is only observed for task-relevant target events with an amplitude maximum over more posterior sites [Hillyard et al., 1971; Squires et al., 1975]. There are numerous models of the potential psychological processes related to the P3, a summary of which is beyond the scope of this paper [Polich, 2007; Verleger, 2020]. The focus of the present study is on the P3b, but the paradigm used will be expected to evoke some P3a as well, which is why we will refer to the response below simply as P3.

Defining the functional role of the P3 in a neuroanatomically constrained model has been limited by ambiguous findings concerning its neural generators: Early intracranial EEG (iEEG) recordings in patients with epilepsy demonstrated P3-like responses in the hippocampus [Halgren et al., 1980], but subsequent studies in patients with lesions of middle temporal lobe structures demonstrated that the hippocampus is not the source of the P3 as measured by scalp EEG [Johnson, 1988; Onofrj et al., 1992]. Further iEEG studies showed that P3-like responses can be observed by electrodes in many other brain areas [Halgren et al., 1995b; Halgren et al., 1995a], and it was suggested that the neural generator of the P3 is distributed across multiple brain areas, including temporal, frontal, and parietal lobes, as well as the cingulate gyrus. This view was further supported by fMRI, which has been used to constrain source models of the P3 recorded in EEG [Bledowski et al., 2004; Li et al., 2020; Linden et al., 1999; Mulert et al., 2004a; Mulert et al., 2004b]. In

agreement with other fMRI studies [Kim, 2014], these constrained source models suggested

potential generators of the P3 in the pre-central sulcus (PCS), intra-parietal sulcus (IPS),

supplementary motor area (SMA), midcingulate cortex (MCC), insular cortex, and temporo-parietal

junction (TPJ). A potential role of the TPJ has been independently emphasized by studies in

patients with structural brain lesions [Knight et al., 1989; Verleger et al., 1994; Yamaguchi and

Knight, 1991]. Source analysis of the P3 in magnetoencephalography (MEG) has typically

suggested sources in the deep [Rogers et al., 1993; Tarkka et al., 1995] temporal lobes, but others

reported that the P3 was not obtained reliably at all in MEG [Siedenberg et al., 1996]. Currently, it

is widely held that the P3 is generated by the same areas observed active during target detection

of rare events in fMRI [Bledowski et al., 2004; Kim, 2014; Mulert et al., 2004b], i.e., in TPJ, dorsal

frontal and parietal cortex, and in the MCC and SMA. In other contexts, however, fMRI has been

suggested to be linked with gamma activity rather than with evoked potentials in lower frequency

bands [Niessing et al., 2005; Steinmann and Gutschalk, 2011], and a detailed investigation of how

activity in defined anatomical areas would generate the spatial distribution of the P3 observed in

EEG and MEG is still lacking.

The present study assessed the neural generators of the P3 by employing combined M/EEG

recordings and source analysis in a classical auditory oddball paradigm [Ritter et al., 1972], and

directly compared such source analysis results to fMRI. Our results suggest a different source

configuration for the P3 than summarized above, with one source lying in retro-splenial cortex

(RSC), and another source lying in insular cortex. This P3 activity is paralleled by activity in multiple

other areas, including auditory cortex (AC), left primary somato-sensory cortex (S1), and anterior

MCC (aMCC), which can be dissociated from the P3 by their activation time courses. In the second

part of the paper, we simulated the scalp EEG and sensor MEG distribution based on circumscribed

sources in these regions to evaluate (i) their contribution to the centro-parietal P3 that is typically

evaluated in EEG, and (ii) to control for the interaction between remote source areas. Finally, we

tested which of the simulated sources can explain the data at the P3 peak. Results suggest that

the source in RSC explains more variance of the data than other sources.

Materials and Methods

Participants

A total of fifteen healthy young adults (female, 8; male 7) with a mean age of 26.8 years (range 20 - 45) with no previous history of neurological or hearing disorder participated in this study. This sample size was based on experience from previous studies using similar source analysis techniques. The data of three participants were excluded later from the analysis due to large measurement artifacts (n=2) and incomplete recording (n=1). The study was approved by the ethics committee of Heidelberg University, Germany and each volunteer provided written informed consent before participation.

Experimental design and procedure

Simultaneous M/EEG data were recorded while presenting a classical auditory oddball sequence consisting of frequent standard (1000 Hz) and rare (14%) deviant (900 Hz) tones. fMRI data were recorded using the same stimuli within a separate session. Tones of 75 ms duration were presented with an average 2-s inter-stimulus interval, randomly jittered by ± 0.5s. A total of 1274 tones were presented across 3 separate runs. Listeners were instructed to press a button with their right index finger to identify all deviant tones. For both M/EEG and fMRI measurements, participants were presented with the same stimuli, with a short break in between the three runs. In MEG, stimuli were presented diotically with ER-3 earphones (Etymotics Research, Elk Grove Village, IL, USA) via foam earpieces. In fMRI, stimuli were presented diotically via MR-compatible S14 insert earphones (Sensimetrics Corporation, Gloucester, MA, USA), which attenuate the scanner noise by approximately 15-20dB. Sound level was individually adjusted to be at a comfortable listening level. All sound stimuli were generated using PsychoPy software (www.psychopy.org) [Peirce, 2007].

Data acquisition

MEG data were acquired at a sampling rate of 1000 Hz (using a 330 Hz online low-pass filter) inside a four-layer magnetically shielded room (IMEDCO) via a Neuromag-122 whole-head system

(MEGIN OY, Helsinki, Finland) equipped with 61 dual-channel planar first-order gradiometers.

Participants' head geometry and location of four head-position indicator coils were digitized

together with the EEG electrode positions relative to a coordinate system spanned by the nasion

and two pre-auricular points using a Polhemus Isotrack II digitizer (Colchester, VT, USA). EEG data

were recorded using an Easycap (Herrsching, Germany) M64 recording cap with a 64-channel

10%-system montage. The EEG was amplified with two 32-channel Neuroscan amplifiers,

referenced to Pz, and digitized together with the MEG.

MRI data were acquired with a 3T Siemens Magnetom Trio scanner (Siemens Medical Systems,

Erlangen, Germany) with a 32-channel coil; fMRI data were acquired with an interleaved echo

planar imaging (EPI) sequence (TR=2 sec, TE=30 ms, flip angle 80°) with 32 axial slices aligned

along the anterior-posterior commissure line (3.99-mm slices, 3×3 mm^2 in-plane resolution).

Structural MRI images with the same field of view were obtained, including T1-weighted anatomical

images (GR/MPRAGE, flip angle 9, echo time 2.63, repetition time 1570, resolution 1×1×1 mm^3)

and multi-echo fast low-angle shot (FLASH) sequences. These images were used for co-

registration with subject-specific M/EEG and fMRI results to standard space and for creating

realistic-shaped boundary-element head models. The three scanning runs lasted 800 seconds

each and there was a brief break after each run to restart the stimulation and communicate with

the participant.

M/EEG data Preprocessing

Preprocessing of M/EEG data was performed using MNE software packages

(http://martinos.org/mne) [Gramfort et al., 2013]. For each recording (three runs per participant),

first, a visual inspection of the raw M/EEG data was carried out to identify and mark time epochs

as well as the channels containing large artifacts or flat signals. A separate denoising was then

performed only for the MEG data to reduce uncorrelated sensor noise and artifacts (i.e., flux jumps)

using oversampled temporal projection (OTP) [Larson and Taulu, 2018]. This technique allows

suppression of sensor-space noise that is spatially uncorrelated with the data. After applying a

bandpass filter (0.5-30 Hz) on the M/EEG data, re-referencing of the EEG was performed to an

average reference. Eye blinks and cardiac artifacts were then removed from the data using MNE's

independent component analysis algorithm [Hyvärinen, 1999]. Afterwards, the data were epoched

from -100 to 1000 ms relative to stimulus onset, yielding two stimulus locked conditions: standard

and deviant. A separate epoching window spanning -500 to 500 ms relative to the button press

was created to track response-locked brain activity. Thus, three overall data conditions were

constructed: standard, deviant, and response-locked. Next, the bad segments of epochs (trials)

were repaired using an automatic data driven autoreject [Jas et al., 2017] algorithm implemented

in MNE. All remaining deviant and response-locked conditions were included in the average

response. The number of averaged standards was reduced to the number of deviants using the

'mintime' function in MNE, to equalize the number of deviant and standard trials for the source

analysis.

The source space and gain matrix

To define an individual, cortically constrained source space, FreeSurfer [Dale et al., 1999; Fischl,

2012] was first used to reconstruct the cortical surface (white and pial) from the high-resolution T1-

weighted scan (3D MPRAGE data) for each participant. Afterwards, at least 10242 dipoles (i.e.,

source locations per hemisphere) were placed at the gray-white matter interface to create the

source space, with ~3 mm spacing. The individual forward solution was restricted to a cortical

source space parcellation, which excludes corpus callosum and areas below that were removed

from the source space. The resulting dipole locations correspond to a cortical surface area of about

10 mm^2 on average. High resolution inner-skull, outer-skull, and scalp surfaces created from

FLASH images were used to model the electrical conductivity between each surface using a three-

compartment boundary-element model (BEM) using MNE. For BEM, 5120 triangles were used for

creating the triangulated meshes with respective conductivities of the brain, skull, and skin were

assumed to be 0.3 S/m, 0.06 S/m and 0.3 S/m. To define the locations of the EEG electrodes on

the scalp and the configuration of the MEG sensors relative to the cortical surface, MNE-coordinate-

system alignment tools [Gramfort et al., 2013] were used, where fiducial landmarks (two pre-

auricular points and the nasion) are manually identified from the MRI-based rendering of the head

surface [Besl and McKay, 1992]. The tool calculates a transformation by minimizing the digitized

scalp surface points with respect to the MRI-defined scalp.

Inverse modeling and source analysis of M/EEG data

The field distribution y(t) of sensor/electrode space M/EEG data can be modeled as a linear

combination of the source time courses x(t) and noise n(t):

168                                   $y(t) = Gx(t) + n(t)$ (1)

where, G is the forward gain matrix. To estimate the source current density on the cortical surface

for each participant, a separate forward solution for each experimental segment was computed in

MNE separately and averaged together [Gramfort et al., 2013; Hämäläinen and Sarvas, 1989;

Uutela et al., 2001] for more accurate source estimation. The inverse estimation of active sources

(x) is then performed by applying an inverse operator (G´) to the data by using the linear L2

minimum-norm estimator (MNE) such that:

175                          $x´ = G´_{MNE}\, y = G^T(GG^T + \lambda^2 C)^{-1}\, y$ (2)

where, x´ is an estimation of the true sources x, C is the noise covariance matrix at the

sensor/electrode space, and λ is the Tikhonov regularization parameter. In addition to that, a loose

orientation constraint of 0.2 was added to the model so that it can remain flexible against co-

registration errors [Lin et al., 2006a] Afterwards, the source estimates were normalized to yield a

dSPM [Dale et al., 2000]. This step was performed for each condition (i.e., standard, deviant,

deviant - standard, and button response) separately. The noise-covariance matrix was calculated

from pre-stimulus baseline i.e., 100 ms preceding the stimuli by using an automated advanced

regularization method called shrinkage technique [Engemann and Gramfort, 2015]. Subsequently,

noise-normalized source-space data from each participant were transformed onto a template brain

atlas i.e., the FreeSurfer average brain (fsaverage) using a spherical registration method [Fischl et

al., 1999]. This registration was used to accurately align the dSPM results across individuals. The

resulting maps across participants were then averaged per evoked condition to create a single

grand-average dSPM solution. For the ROI-based analysis, hand-drawn ROIs were defined on the

FreeSurfer average brain based on the anatomy and were then transformed to the individual brain

anatomy; ROIs were placed on one side of a sulcus and not across sulci, such that most dipoles

within the ROI are expected to have similar dipole orientation and thus polarity. Time-courses per

condition were then calculated as average across all dipoles within each ROI, separately for each

individual participant. Note that defining a one-polarity ROI for Heschl's gyrus can be complex,

because there is often a polarity reversal towards Heschl's sulcus (between Heschl's gyrus and

planum temporale). We therefore also explored separate ROIs for the anterior and posterior half of

Heschl's gyrus. Because these ROIs revealed similar results for the data of this study, we restricted

our analysis to a single ROI defined for the middle of Heschl's gyrus, avoiding the posterior border

towards Heschl's sulcus and the anterior border towards the circular sulcus.

Spread analysis of M/EEG data

The point-spread function (PSF) and cross-talk function (CTF) [Hauk et al., 2011] were computed

in order to characterize the leakage of current estimates between different ROIs. First, the dSPM-

based resolution matrix was computed by multiplying the inverse operator to the forward gain

matrix for each ROI. Afterwards, each ROI based PSF and CTF was extracted as the column and

the row of that resolution matrix, respectively. This step was then repeated for all individual data

set before averaging across participants. Finally, leakage of current estimates and the potential

influence of one ROI to another were calculated as the absolute correlation between ROIs for PSFs

and CTFs.

Statistical tests and reproducibility

The statistical difference among ROI-based source-level time courses between standards and

deviants was assessed through a two-sample cluster-based permutation test [Maris and

Oostenveld, 2007] across participants. The statistical test is a non-parametric test that is designed

to solve the multiple comparisons problem (MCP) during hypothesis testing. In detail, first, an F

statistic is computed at each participant-specific ROI-based source-space data sample (every 2 ms

from -100ms to 1000ms relative to stimulus onset) from each data condition. A cluster threshold (p

< 0.01) drawn from a standard F distribution was then applied at each sample, keeping only the

statistically significant samples to form clusters whose values were higher than the applied

threshold. Afterwards, the cluster-level statistic is defined within each cluster by taking the sum of

its absolute test statistics. Then, a maximum cluster-level permutation distribution was constructed

by using the cluster statistics computed under a Monte Carlo estimation [Ernst, 2004] with random

shuffling and 100001 iterations. Cluster level p-values were estimated by computing the proportion

that resulted in some larger cluster-level statistics than the actual one calculated from the maximum

cluster-level permutation distribution. Significant cluster p-values were defined by correcting the p-

values using a Bonferroni correction i.e., critical alpha level ($\alpha = 0.05$) was set to ($\alpha^* = \alpha/n < 0.0025$,

where n=20; 10 ROIs x both hemispheres).

fMRI data processing

For each participant, the functional volumes were mapped on the high-resolution anatomical

surfaces using FreeSurfer. Surface-based fMRI data processing was then carried out using a

standard FS-FAST routine (FreeSurfer's functional analysis stream tool) [Fischl, 2012]. First,

preprocessing of the fMRI data was performed that includes the following sequence: template and

brain-mask creation, followed by the registration of the functional data with FreeSurfer anatomical

structure, motion correction, slice timing correction, intensity normalization of all voxels and time

points, resampling of the data to the FreeSurfer average brain (fsaverage) atlas, and spatial

smoothing of the data by a 5mm Full-Width/Half-Max (FWHM). Next, first level time series analysis

of the data was performed for each participant to remove nuisance variables (i.e., head motion)

before computing p-values for a contrast between deviant and standard experimental conditions

based on individual participant's time courses with a canonical SPM hemodynamic response

function. Later, a random-effects group analysis was performed across participants by using a

Generalized Linear Model (GLM) implemented in FreeSurfer [Fischl, 2012], followed by a multiple

comparisons correction with the false-discovery rate (FDR, $p<0.05$) [Genovese et al., 2002]

method. fMRI data processing steps were carried out for the left hemisphere and right hemisphere

separately.

Cortical M/EEG source simulations

Bilateral, anatomically constrained sources were simulated for each participant's cortical surface

mainly based on the ROI already used for the time-course analysis. First, each ROI defined on the

FreeSurfer average brain was transformed to the individual brain anatomy. For each anatomical

ROI, all dipolar sources lying within were uniformly activated with a time-course of a half-sinusoidal

wave composed with a base frequency of 5 Hz. The amplitude of each individual dipole was then

scaled such that the absolute value summed over all dipoles within a single ROI amounted to 25

nAm peak. The polarity of the sources was assigned as positive- or negative-going for each

ROI with reference to the cortical surface. For each ROI, a source in the left and right hemisphere

were combined to yield a bilateral source configuration. Only for S1, the simulation was limited to

a source in the left hemisphere. To simulate realistic sensor level noise, the individual noise-

covariance matrices based on the M/EEG data were used and scaled to a number of 200 averages.

The simulations were then analyzed as described above for the experimental data, separately for

each ROI used for the simulation. Individual scalp-EEG, sensor-MEG, and cortical dSPM source

estimates were computed at the peak of the simulated source for each individual data set and then

averaged across all 12 simulated data sets.

Explaining experimental data by simulated activity

Linear combinations of the simulated M/EEG patterns from the previous paragraph were used to

explain the scalp/sensor-level M/EEG data. The M/EEG data were averaged across subjects at the

individual peak latency of the P3 in EEG electrode Pz and in Cz for the N1. The relative weighting

of each simulated ROI component was determined with a least-squares procedure to best explain

the M/EEG data. This can be written as:

$$\text{Simulated M/EEG} = \arg\min \left(\Sigma_i W_i\, x_i(n) - y(n) \right)^2 \qquad (3)$$

Where, W is the latent weighting vector for each (bilateral) ROI, $x(n)$ is the ROI-based M/EEG

simulation, and $y(n)$ is the P3 (N1) data.

For this procedure, the MEG and EEG data were normalized relative to the standard deviation and

mean of the pre-stimulus baseline interval (i.e., MEG and EEG data were transformed to a z score),

keeping the relative amplitudes within MEG and EEG data intact. To control for linear dependence,

a multi-collinearity test was carried out by calculating the variance-inflation factor (VIF) across the

ROI-based M/EEG simulations. VIF cutoff for linear independence was set to 5, i.e., all ROI

combinations with a VIF value of less than 5 were considered linearly independent.

To quantify the quality of each model, the residual variance (RV) was calculated between the P3

(N1) data and the weighted combination of ROI-based simulations. The weights provided in the

table represent the weight W multiplied by 25 nAm, which was the strength of the summed

simulated activity within each source. In this scaling, the weights provide a rough estimate of the

source strength underlying the activity in the respective ROIs at the P3 (N1) peak latency. Note

that this source strength does not equal the strength of a single dipolar source, since the variable

geometry of ROIs cause different degrees of signal cancelation within each multi-dipole source.

Results

A standard auditory oddball paradigm was used with the main goal of providing a high signal-to-

noise ratio for source analysis. The paradigm comprised repeated, frequent 1000 Hz standard

tones and rare 900 Hz deviants, which participants detected by button press. The average hit rate

across subjects in M/EEG was 97±3% and mean reaction time 507±103ms (mean ± standard

deviation). In fMRI the hit rate was 99±4% and the reaction time 490±150ms.

At the electrode and sensor levels (Figure 1a), the two most prominent peaks of the event-related

response are the central negativity around 100 ms (N1) in both deviants and standards, and the

prominent centro-posterior positivity around 400 ms (P3) evoked by deviants (targets). While this

P3 is readily evident as the biggest response in the EEG deviant waveforms around 400 ms, the

N1 is more prominent in MEG. When averaging is aligned to the onset of the button press instead

(Figure 1b), the EEG shows a slow and steady increase up to about 40 ms after the button press,

whereas MEG activity shows a steeper increase right after this event. Thereafter, EEG and MEG

similarly show a slow and steady decrease. Maps of the EEG and MEG distribution at the individual

maximum at Pz are highly similar when compared between the stimulus- and response-locked

versions of the P3, with some differences in the left hemisphere that are more prominent in MEG

(Figure 1c).

Figure 1 Grand-average evoked-response waveforms and maps. (a) Stimulus-locked EEG waveforms (left)

and MEG waveforms (right) for standards (black) and deviants (orange). While the N1 is observed for

standards and deviants alike, activity in the P3 time window from 300 – 600 ms is only observed for deviants.

(b) Waveforms averaged to the button press for detected deviants. While the EEG (left) is dominated by an

increasing signal slightly beyond the button press, the MEG (right) shows a particularly strong, steeply rising

response after the button press, corresponding to the somato-sensory feedback. c Grand average EEG maps

(upper) and reconstructed MEG magnetometer maps (lower) at the peak latency of the N1 (left), the P3

(middle), and the response-locked P3 (right). Individual peak latencies for mapping were determined at

electrode Cz for N1 and at electrode Pz for response-locked P3.

Source analysis of the P3 in comparison to fMRI

Figure 2 Cortical M/EEG and fMRI activation maps. (a) Combined M/EEG dSPM maps for deviants (upper),

standards (middle), and the contrast deviants – standards (lower) in three different time windows (p<0.01).

The early 75 – 125 ms time window (T1) is focused on the N1, the middle 300 – 500 ms time window (T2) on

the P3, and the late 500 – 800 ms time window (T3) on the late frontal negativity. Because the dSPM maps

are based on a fixed-effects statistic, the number of standard trials was reduced to the number of deviant trials

for this analysis. (b) dSPM maps for the response-locked average in the time window 50 ms before and 50

ms after the button press. (c) fMRI maps for the contrast deviants – standards (p<0.05, FDR corrected), based

on a random-effects statistic.

To obtain reliable source models for the P3, the raw M/EEG data were first meticulously pre-

processed to exclude, and model known artifact sources. Source analysis of the evoked response

was obtained by calculating dynamical statistical parametric maps (dSPM) [Dale et al., 2000] in an

individual cortical source space, and a dSPM across subjects was then calculated after morphing

the individual source estimates onto the Freesurfer average brain. The results of this procedure are

shown in Figure 2a. In the early N1 time range (T1: 75 – 125 ms), source activity is observed in AC

on the superior temporal plane with spread to adjacent and medial areas, including the inferior

parietal lobes, superior temporal sulcus, medial temporal lobes, and posterior MCC (pMCC). For

deviants, AC activity persists into the P3 time range (T2: 300 – 500 ms), but the activation pattern

somewhat changes its distribution and extends more anteriorly towards the insular cortex then.

Moreover, consistent activation is observed in the retro-splenial cortex (RSC) and in the posterior

cingulate cortex (PCC) [Vogt et al., 1995; Vogt, 2019]. The RSC and PCC are opposite to each

other, lying on the ventral and dorsal bank of the cingulate gyrus, respectively. Accordingly, the

polarity with respect to the cortical surface is positive in PCC and negative in RSC, suggesting that

only one of the two is the biophysical generator. This activity continues into the later time window

(T3:500 – 800 ms), in which additional activity is observed in anterior MCC (aMCC; previously

subsumed to ACC [Vogt et al., 1995; Vogt, 2019]). This aMCC activity is of opposite orientation to

PCC/RSC, i.e., negative in the dorsal and positive in the ventral bank of aMCC. Qualitatively similar

source analysis results were also obtained by application of other widely used source estimation

methods (Figure S1) including standardized low-resolution brain electromagnetic tomography

(sLORETA) [Pascual-Marqui R D, 2002] and the unit-noise gain minimum variance beamformer

(Borgiotti-Kaplan beamformer) [Sekihara and Nagarajan, 2008].

We also evaluated the activity with respect to the button presses indicating correct target detection

(Figure 2b). These response-locked maps overall show similar activation patterns as the stimulus-

locked maps in the 50 ms before the button press. In the 50 ms after the button press, as expected,

the activity around left S1 is much stronger. No significant motor-cortex activity, peaking before the

button press, was observed.

The same auditory oddball paradigm was employed in an fMRI experiment, to directly compare

M/EEG and fMRI maps. The fMRI results for the deviant-minus-standard contrast (p<0.05, Figure

2c) confirmed previous reports [Bledowski et al., 2004; Kim, 2014] of extensive brain activation for

oddball, or generally target detection, with activity in frontal, parietal, and temporal lobes, as well

as extensive activation in midline structures around MCC and SMA. When comparing the difference

maps for M/EEG (Figure 2a) and fMRI (Figure 2c), it becomes evident that only part of the sites

identified by fMRI also show significant source activity in M/EEG, including AC, MCC, S1, and

probably insular cortex. Strong fMRI activity is also observed in RSC, but not in PCC. Based on

this intramodal comparison, it would therefore appear that the M/EEG activity is also more likely

generated in RSC. When the fMRI activity is thresholded more conservatively (Figure S2), it

appears that the most robust foci of activity are the RSC, aMCC/SMA, insular cortex, auditory

cortex, and TPJ. This pattern is quite similar to the M/EEG source analysis, with the exception of

TPJ, where no significant activity was observed in the source analysis.

Source time courses of M/EEG

In order to explore the temporal characteristics of the prominent M/EEG sources in more detail, we

calculated source-level time courses for regions of interest (ROI) in the RSC, dorsal aMCC, AC

(Heschl's gyrus), insular cortex, and the hand area of S1. As can be observed in these stimulus-

and response-locked time courses (Figure 3a and Figure 3b), the ROIs segregate a number of

distinct neural processes by their timing. Activity in AC shows the typical N1 waveform. Subsequent

to the N1, there is a sustained field that is significant in the deviant-minus-standard comparison on

the left. Typical P3-like time courses are observed in RSC and insular cortex, and with longer

latency in aMCC (note that the orientation of the RSC and aMCC sources are opposite to each

other and that only the RSC produces a positive-going field at Pz)

Figure 3 ROI-based source waveforms. Source waveforms based on dSPM, calculated for the ROIs shown

in the middle column using the same color code. The ROIs include auditory cortex (AC), anterior insular cortex

(insula), primary somatosensory cortex (S1), retro-splenial cortex (RSC), and anterior mid cingulate cortex

(aMCC). (a) stimulus-locked source time courses, averaged relative to tone onset. Typical P3 source

waveforms are observed in RSC (purple) and insula (orange). The orange bar indicates the time interval in

which the deviant and standard responses are significantly different from each other (cluster-based

permutation test, see methods for details). (b) response-locked source time courses shown in similar

configuration.

An interpretation of the P3 as a build-to-threshold process suggests a response increase until

(briefly after) the motor response [O'Connell et al., 2012; Twomey et al., 2015]. The present data

show a similar response shape directly at the source level in RSC and insular cortex. Note that the

stimulus and response locked variants are of approximately similar amplitude, which is compatible

with the hypothesis that the P3 is neither locked to the stimulus nor to the response, but represents

a mapping between the two [Asanowicz et al., 2020; Verleger et al., 2014]. In contrast, activity in

S1 shows a prominent transient wave that peaks approximately 40 ms after the button press, most

likely representing tactile and proprioceptive somatosensory feedback related to the button press.

A small transient after the button press is also observed in left AC; the latency of this wave coincides

with the activity in S1, suggesting that it is spread from or coactivation with S1 rather than auditory

evoked activity related to the button press. Finally, activity in aMCC increases rapidly around the

button press and persists for more than 300 ms thereafter, suggesting a closer relationship to the

task response than to the auditory stimulus.

Comparison with simulated source data

Next, to evaluate the relationship between neural sources, spread of the source estimates, and

scalp/sensor distributions, we simulated (i) the source analysis and (ii) the scalp/sensor distribution

that would be generated by activity at the different ROIs based on the individual anatomy of the

study participants. Each simulated source had a summed source current of 25 nAm (see methods

section for details). As expected, these simulations reproduce the spread that is observed for a

focal source to neighboring sulci, for example to the inferior parietal lobe and to the superior

temporal sulcus in the case of activity in the primary AC (Figure 4a). Spread from AC is also

observed in the medial temporal lobe around the hippocampal gyrus and in the pMCC, matching

the activity pattern observed at the peak of the N1 in the original data (Figure 2a). This suggests

that the data in the 75 - 125 ms time window can be explained with bilateral sources in AC.

Some spread is also observed from AC to insular cortex and vice versa. The positive-going activity

in insular cortex is not explained by spread from Heschl's gyrus, however, suggesting that this

activity observed in the P3 time window is really generated in insular cortex.

To quantify the interaction between the evaluated brain regions in the dSPM source analysis, we

calculated the point-spread function and cross-talk function between ROIs (Figure 4c; Figure S3

and Figure S4). A strong interaction between sources within one hemisphere is observed between

(1) Heschl's gyrus and hippocampal gyrus, (2) insular cortex and aMCC, and (3) insular cortex and

hippocampal gyrus. Strong spread is also observed between RSC and contralateral aMCC. Spread

between left S1 and AC is also confirmed by this analysis, which explains the S1-like waveform for

response-looked waveforms in AC (Figure 3a). In contrast, there was comparatively little spread

between AC and insular cortex ROIs.

Figure 4 Simulated M/EEG and analysis of spread. (a, b) The data represent an average of n=12 individual

simulations, based on bilateral, individually morphed ROIs in auditory cortex (AC), Insula, medial temporal

cortex (MT), retrosplenial cortex (RSC), and anterior middle cingulate cortex (aMCC). The simulation of the

primary sensory hand area (S1) is based on a single, left sided ROI. Source polarity was chosen to match the

pattern observed in the N1 (AC, MT) or P3 (insula, S1, RSC, aMCC) time window shown in Figure 2. (a) dSPM

based source mappings of the simulated M/EEG data (p<0.01). (b) Scalp/sensor level maps of the grand-

average simulated EEG (upper) and MEG (lower), same scaling for all conditions. (c) Point-spread analysis

(upper circle) and cross-talk analysis (lower circle) for the same ROIs used in (a) and (b). Each analysis is

visualized using a circular graph with an absolute arbitrary correlation cutoff value of 0.25. The exact values

are summarized in Figure S3 (point spread) and Figure S4 (cross-talk).

The RSC source produces a symmetric, posterior EEG scalp distribution that matches well with

main aspects of the typical P3 observed in our data (Figure 1c). In comparison to EEG, the

simulated MEG activity for an RSC source is relatively weak, which could be related to the difficulty

of recording P3 in MEG reported previously [Siedenberg et al., 1996]. However, the MEG simulation

does not match well with the measured MEG map at the P3 peak (Figure 1c). Moreover, the P3-

peak maps showed higher reproducibility in EEG at the individual level, and much more variability

in MEG (Supplementary Figures 5 and 6). These data indicate that the explanation of the EEG and

in particular the MEG data requires multiple sources, for which MEG and EEG supposedly have

different sensitivity.

Explaining the P3 with simulated M/EEG data

We therefore explored how the combined M/EEG P3 data can be explained by a combination of

the sources that were used for the time-course analysis. To quantify the relative contribution of

potential sources, the simulations based on the ROIs used for the time-course analysis were fitted

with a least-squares procedure to the P3 data at its peak. The results show that a reasonable

explanation of both EEG and MEG data can be achieved with this procedure (Figure 5), leaving

6% residual variance in EEG and 62.5% residual variance in MEG (Table 1). Among all five

sources, the RSC was scaled to the highest amplitude. When one of the sources was systematically

omitted from the model, a massive increase of residual variance in EEG was only observed with

the RSC omitted. Note that omitting RSC also led to the strongest increase of residual variance in

MEG, supporting that the relatively weak contribution of the RSC is still relevant for MEG. All other

sources only caused weak increment of the residual variance in EEG when omitted. This was also

the case for the S1 source, the omittance of which increased the residual variance by only 0.4% in

EEG, but by 19% in MEG, demonstrating that this source is almost as important for the MEG maps

as the RSC at the P3 peak.

To test the validity of the modeling approach, the same sources were fitted to the N1 data, leading

to zero weights for all sources except for AC and insula (Figure 5; Table S1). This model resulted

in a residual variance of 16.3% in EEG and 27.8% in MEG. While the weighting of the insular cortex

of about 1/3 of the auditory cortex appears relatively high, leaving out the insular ROI leads only to

a minor increase of the residual variance, whereas the insular cortex alone cannot explain the N1

data well.

Figure 5 Multi-source simulation for the stimulus-locked N1 and P3. (a) Grand average EEG maps and

reconstructed MEG magnetometer maps at the peak latency of the N1 in EEG (upper). Combined simulation

of N1 maps in scalp/sensor space based on the sum of the sources (AC and insula; see Table S1) fitted to

the stimulus-locked N1 (lower). (b) Grand average EEG maps and reconstructed MEG magnetometer maps

at the peak latency of the P3 in EEG (upper). Combined simulation of P3 maps in scalp/sensor space based

on the sum of the sources (AC, insula, S1, RSC, and aMCC; see Table 1) fitted to the stimulus-locked P3

(lower).

Note that the values of the residual variance of these models must not be directly compared

between MEG and EEG. First, higher residual variance in MEG is generally expected based on the

more focal signal in planar gradiometers, which leaves other sensors with less signal but similar

noise. Second, the relative weighting of MEG and EEG is based on Z-scores, which then results in

an advantage for EEG because of higher signal to noise level. The relative amplitude of MEG and

EEG simulations depends on assumptions made in the head model, in particular the conductivity

of the EEG model, which is individually different and difficult to estimate exactly. As a consequence,

the amplitude of the MEG is somewhat underestimated by the model, for both N1 and P3, which is

an additional source of higher residual variance in MEG compared to EEG.

Table 1 Modeling the grand-average P3 data with simulated M/EEG based on anatomically defined

source regions (Figure 4b).

	Simulated source activation patterns					Residual variance (RV) (%)	
	AC	Insula	S1	RSC	aMCC	EEG	MEG
Source strength (nAm)	5.50	7.75	11.25	44.25	12.75	6.0	62.50
	-	3.0	12.75	42.0	20.25	6.0	65.30
	3.50	-	11.75	42.0	17.75	5.0	67.0
	9.25	11.25	-	49.75	16.25	6.40	81.50
	0.0	0.0	22.75	-	4.0	52.90	87.10
	10.25	15.50	12.0	45.0	-	8.30	60.50

Finally, we tested two previous hypotheses for the generation of P3, which were not suggested by

the dSPM analysis. First, a source in TPJ has been suggested based on fMRI, fMRI-constrain

EEG, and lesion studies [Bledowski et al., 2004; Knight et al., 1989]. To this end, we used the

region provided by a standard parcellation [Destrieux et al., 2010]. Such a bilateral TPJ source

produces a bilateral posterior maximum (Figure S7b), but cannot replace the RSC in direct

comparison. When added as the sixth source to the model from Table 1, TPJ receives no weight.

When TPJ is used to replace RSC in a model with five sources, the residual variance increases to

50.4% in EEG and 85.4% in MEG, providing no support for a relevant contribution of TPJ to the P3

in the present data.

Second, a previous EEG study suggested that a distributed source in superior parietal cortex

[Moores et al., 2003] could explain the P3. For this simulation, it was assumed that a distributed

source existed right below the centro-posterior P3 in the EEG map, extending down to the IPS with

a homogeneous amplitude distribution. This extended source indeed produces an EEG pattern with

considerable similarity to the centro-posterior P3 (Figure S7b), as well as to the RSC simulation.

Replacing the RSC with this distributed source accordingly produces only slightly higher residual

variance in comparison (Table S2). It is interesting to note that the dSPM estimate of this simulated

source shows considerable spread to the RSC and PCC (Figure S7a), but, conversely, no strong

activity in parietal sulci was observed in the P3 source analysis, as would have been predicted by

this simulation.

Discussion

Our results provide evidence of a role for RSC [Vogt et al., 1995; Vogt, 2019] in the generation of

the classical P3. A second source with a typical P3 time course was observed in insular cortex, but

this component was not dominant for the M/EEG maps. Other sources like S1, AC and aMCC are

active in an overlapping time range but contribute to different aspects of the evoked response,

which we do not consider part of the classical P3. This model is at odds with the long-held

assumption that the P3 as observed by M/EEG is generated by a more distributed set of sources

[Bledowski et al., 2004; Mulert et al., 2004b] that is not well accessible to source analysis

techniques. The results are based on the combination of EEG, MEG, and individual anatomy to

provide the best possible information for the source analysis [Molins et al., 2008]. Conversely, we

did not directly constrain the source analysis with information from fMRI [Bledowski et al., 2004]. In

our view, caution is warranted when using such priors unless correlation between the brain activity

measured by the different modalities has been independently confirmed; otherwise, such priors

have the potential to mislead M/EEG analyses and lead to incorrect inferences regarding M/EEG

sources. Indirectly, however, we used the information provided by fMRI, which first confirms that

the RSC is active during target detection, and second allows for the disambiguation of the ventral

RSC from the dorsal PCC, an inference that cannot be easily made based on the M/EEG data

alone.

The limitations of the inverse problem remain, though, and alternative source models can easily be

constructed. For example, an extended positive-going source directly below the P3 maximum in

the EEG map produced a very similar map and could be used to substitute the RSC source in our

model. A previous EEG study that used minimum-norm source reconstruction without noise

normalization had proposed such a solution [Moores et al., 2003]. However, the latter method

generally prefers superficial sources [Lin et al., 2006b], which is balanced by noise normalization

as used in the present study. One further difficulty of M/EEG source analysis is that, in contrast to

fMRI, the distribution of a source is not directly related to the actual extent of the activity on the

cortex. The pattern with opposite polarity with respect to the (outward) cortical normal in adjacent

banks of a sulcus is often caused by spread of a focal source (Figure 4b), whereas a physiological

source that extends across both banks with the same polarity would lead to major signal

cancelation for distant recordings in M/EEG [Goldenholz et al., 2009]. We therefore chose to display

source activity together with polarity information, to avoid the impression of extended sources

where they are unlikely, based on the activation pattern, and estimated the spread and activation

pattern of each source by simulation studies.

The other limitation is the degree to which fMRI can be used to constrain M/EEG source analysis.

All sources that were found active in the dSPM maps of this study were also confirmed by fMRI,

but fMRI shows activity in additional areas that were not revealed by M/EEG source analysis. There

are at least two potential sources for this discrepancy: First, electric activity of similar surface

polarity cancels out for M/EEG if the source spans two sides of a sulcus [Ahlfors et al., 2010],

whereas this configuration would rather support the activity's detection in fMRI. This could e.g.,

apply to potential sources in the IPS or TPJ; it could then be that there was another P3 source in

this region, but that its signal-to-noise ratio was low for M/EEG. Second, fMRI often does not match

with low-frequency M/EEG activity in the delta and theta band such as e.g. the error-related

negativity [Agam et al., 2011], but better with neural activity in the gamma band [Logothetis et al.,

2001; Niessing et al., 2005; Steinmann and Gutschalk, 2011]. Thus, while the strong RSC activity

in fMRI generally supports the RSC's contribution to the P3 source, it still remains possible that the

relationship between M/EEG and fMRI activity in this region is indirect, e.g., via functionally coupled

gamma activity.

Activity in the PCC and RSC has also been reported in intracranial recordings of the P3 [Halgren

et al., 1995b], without providing a clear separation between the two. While the authors of that study

suggested that the PCC/RSC was a source of the P3a rather than the P3b, neither fMRI [Kim,

2014] nor source-analysis studies [Bledowski et al., 2004] have confirmed such a strict separation

of P3 subcomponents as suggested based on these intracranial data. As a limitation, while the

depth recordings found high amplitudes in and near PCC, no polarity reversal was found [Halgren

et al., 1995b], which would have confirmed that the electrode passed through the source.

Another constraint for a potential P3 source in RSC is how this region is connected to other brain

networks recruited by target processing. The PCC has been demonstrated to be a major hub of the

"task-negative" default-mode network [Fox et al., 2005], while activation during oddball detection

[Kim, 2014] has been observed in "task-positive" networks [Fox et al., 2005; Hugdahl et al., 2015]

such as the dorsal and ventral attention networks [Yeo et al., 2011]. In the early resting-state

network studies, PCC activation included all of RSC [Fox et al., 2005], whereas later, more detailed

network maps [Yeo et al., 2011] segregated the dorsal part of RSC into a fronto-parietal network,

which would better match with a role in active target detection. Anatomical studies in monkeys

indicate that both PCC and RSC are reciprocally connected with multiple frontoparietal areas that

are active during oddball tasks in fMRI [Kobayashi and Amaral, 2007; Vogt and Pandya, 1987].

This would be consistent with the idea that even if the fronto-parietal network does not itself

generate the P3, it may still be functionally coupled with a generator in RSC. Such connectivity

would explain previous findings of reduced P3 with right-TPJ lesions [Knight et al., 1989; Verleger

et al., 1994], even if TPJ was not the source of P3. In fact, a model where TPJ provides input into

RSC, the neuroelectric source of P3, could better explain why unilateral TPJ lesions caused

bilateral reduction of the P3 [Knight et al., 1989].

The RSC is also functionally coupled to the hippocampus in the medial temporal lobe [Alexander

et al., 2018]. Given the hippocampal P3-like activity demonstrated by iEEG [Halgren et al., 1980],

this raises the possibility of a close functional coupling between the extracranial P3 in M/EEG and

the intracranial hippocampal activity, despite their anatomical dissociation. Another important

question for the source analysis and simulation studies was if hippocampal P3-like activity could

potentially be recorded in M/EEG. Despite its clear demonstration in iEEG [Halgren et al., 1980],

no hippocampal activity has been shown in fMRI in this (Figure 2c) or previous odd-ball-paradigm

fMRI studies [Kim, 2014]. One possible reason for this negative finding could be different neuro-

vascular coupling in medial temporal lobe compared to neocortex [Hill et al., 2021], suggested

recently based on combined iEEG and fMRI. While the contribution of a hippocampal source to the

parietal P3 in EEG had already been excluded based on lesion studies [Johnson, 1988; Onofrj et

al., 1992], this does not exclude that hippocampal activity may generally contribute to other aspects

of the M/EEG response [Alberto et al., 2021], even though with only a weak signal-to-noise ratio.

Indeed, the mapping shown in Figure 2 also suggests activity in the medial temporal lobe. However,

this activity was as prominent in the N1 as in the P3 time interval, which is not consistent with

known iEEG time courses in hippocampus [Halgren et al., 1980]. Moreover, we demonstrated that

there is considerable spread and crosstalk between the medial temporal lobe and AC as well as

insular cortex (Figure 4). It is therefore more likely that the activity observed in the medial temporal

lobe in our source analysis represents spread from AC and insular cortex, particularly given the

fact that M/EEG signal-to-noise ratio is much higher in AC (and somewhat higher in insular cortex)

than in the hippocampus [Goldenholz et al., 2009]. This leaves us with the paradoxical situation

that there is strong iEEG evidence for P3-like activity in the hippocampus evoked by the paradigm

used [Halgren et al., 1980], but that this activity is hard to detect or to distinguish from other sources

with all three non-invasive techniques used in this study.

The situation is somewhat different for the insula. While there is also spread from AC to the insula

(or its vicinity) in the N1 time interval, the pattern is clearly different in the P3 time interval, with

surface-positive activity in the insular cortex; activity in AC remains surface negative in this time

interval, as reported previously for a passive oddball paradigm [Kretzschmar and Gutschalk, 2010].

We therefore consider it more likely that the P3-like time course shown in Figure 3 is generated in

the insula, rather than in the temporal lobe. P3 generators in the insula have been suggested

before. An EEG study [Bledowski et al., 2004] suggested a contribution of insular cortex to the P3a.

A recent iEEG study demonstrated a stronger P3b in anterior insular cortex [Citherlet et al., 2020],

in synchrony with gamma activity in the same latency range. Given the observation of strong fMRI

activity for detected oddballs in insular cortex, this supports the hypothesis stated above that

gamma is a potential link between the P3 and BOLD activity. Finally, strong fMRI activity was

observed in aMCC. Insular and aMCC activity are often observed together in fMRI [Yeo et al.,

2011], but the time course of the insula and aMCC found here are quite different: the insular time

course is similar to the RSC and shows a build-up towards the time of the button press. In contrast,

aMCC activity was most prominent after the button press and may thus rather indicate some kind

of performance control [Heilbronner and Platt, 2013].

At this point, this source analysis is limited to a single paradigm, the classical auditory oddball

paradigm. The dominant component in this paradigm is the P3b, but it can be expected that some

P3a source activity will also be present. Therefore, we cannot as yet make strong conclusions with

respect to the neural sources of these subcomponents. The EEG distribution of the simulated

bilateral RSC source over centro-parietal electrodes, however, makes it a better fit for the P3b

rather than the P3a [Polich, 2007]. If other sources are more specific for the P3a [Halgren et al.,

1995a] or show strong overlap between these two subcomponents [Kim, 2014] will require further

studies that manipulate the relative strength of these components. Other, more complex tasks will

certainly be expected to involve additional brain regions. While we propose that the P3 generator

in RSC will remain a constant contributor for such paradigms as well, this hypothesis requires

evaluation in future experiments or the reevaluation of existing data.

Conclusion

Multiple neural processes are active in parallel with the P3 in M/EEG, some observed more easily

with fMRI and some more easily with EEG or MEG. But while the P3 is most likely functionally

coupled to this distributed neural network, it does not appear to be the bioelectric source of the

classical, parietal P3 signal measured in EEG. Based on the evidence presented here, this source

appears to be more focal and to lie in the RSC. This finding is essential to explore the functional

role of the P3 between the fronto-parietal network observed in fMRI [Kim, 2014] and the

hippocampal P3-like activity demonstrated with iEEG [Halgren et al., 1980], and will help to better

understand the functional roles of both RSC and the P3. Moreover, understanding its functional

anatomy may support the application of the P3 as diagnostic tool. For example, reduced P3 in

Alzheimer's disease [Frodl et al., 2002] might be linked to cortical hypometabolism and tau

accumulation [Strom et al., 2022], the latter of which has been suggested to covary with the

connectivity between RSC and hippocampus [Ziontz et al., 2021]. We hope that future invasive

studies will seek to confirm the source configuration suggested by this non-invasive study, possibly

by demonstrating co-occurrence of (high-)gamma activity together with a typical P3 time course in

RSC.

Author contributions

Diptyajit Das: Conceptualization, Formal Analysis, Data Curation, Visualization, Writing - Original

Draft; **Marnie E. Shaw:** Conceptualization, Investigation, Writing - Review & Editing; **Matti S.**

Hämäläinen: Validation, Writing - Review & Editing; **Andrew R. Dykstra:** Validation, Writing -

Review & Editing; **Laura Doll:** Validation, Writing - Review & Editing; **Alexander Gutschalk:**

Conceptualization, Supervision, Validation, Writing - Original Draft & Editing, Funding acquisition.

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Conflict of interest statement

The authors declare no competing financial interests.

Data availability

The processed M/EEG and fMRI data and scripts will be made available on heiDATA, the open research data repository of Heidelberg University under the following doi (not yet published): https://doi.org/10.11588/data/YB9SQI

References

Agam Y, Hämäläinen MS, Lee AKC, Dyckman KA, Friedman JS, Isom M, Makris N, Manoach DS (2011): Multimodal neuroimaging dissociates hemodynamic and electrophysiological correlates of error processing. Proc Natl Acad Sci U S A 108:17556–17561.

Ahlfors SP, Han J, Lin FH, Witzel T, Belliveau JW, Hämäläinen MS, Halgren E (2010): Cancellation of EEG and MEG signals generated by extended and distributed sources. Hum Brain Mapp 31:140–149. http://www.ncbi.nlm.nih.gov/pubmed/19639553.

Alberto GE, Stapleton-Kotloski JR, Klorig DC, Rogers ER, Constantinidis C, Daunais JB, Godwin DW (2021): MEG source imaging detects optogenetically-induced activity in cortical and subcortical networks. Nat Commun 12:5259. http://dx.doi.org/10.1038/s41467-021-25481-y.

Alexander AS, Rangel LM, Tingley D, Nitz DA (2018): Neurophysiological signatures of temporal

coordination between retrosplenial cortex and the hippocampal formation. Behav Neurosci

132:453–468.

Asanowicz D, Gociewicz K, Marcin K, Finc K, Bonna K, Cleeremans A, Binder M (2020): The

response relevance of visual stimuli modulates the P3 component and the underlying

sensorimotor network:1–20.

Besl PJ, McKay ND (1992): A method for registration of 3D shapes. IEEE Trans Pattern Anal

Mach Intell 14:239–256.

Bledowski C, Prvulovic D, Hoechstetter K, Scherg M, Wibral M, Goebel R, Linden DEJ (2004):

Localizing P300 generators in visual target and distractor processing: a combined event-

related potential and functional magnetic resonance imaging study. J Neurosci 24:9353–

9360.

http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&li

st_uids=15496671.

Chaudhary U, Birbaumer N, Ramos-Murguialday A (2016): Brain-computer interfaces for

communication and rehabilitation. Nat Rev Neurol 12:513–525.

Citherlet D, Boucher O, Tremblay J, Robert M, Gallagher A, Bouthillier A, Lepore F, Nguyen DK

(2020): Spatiotemporal dynamics of auditory information processing in the insular cortex: an

intracranial EEG study using an oddball paradigm. Brain Struct Funct 225:1537–1559.

https://doi.org/10.1007/s00429-020-02072-z.

Dale a M, Fischl B, Sereno MI (1999): Cortical surface-based analysis. I. Segmentation and

surface reconstruction. Neuroimage 9:179–194.

http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&li

st_uids=9931268.

Dale AM, Liu AK, Fischl BR, Buckner RL, Belliveau JW, Lewine JD, Halgren E (2000): Dynamic

Statistical Parametric Mapping. Neuron 26:55–67.

Destrieux C, Fischl B, Dale A, Halgren E (2010): Automatic parcellation of human cortical gyri and

sulci using standard anatomical nomenclature. Neuroimage 53:1–15.

http://dx.doi.org/10.1016/j.neuroimage.2010.06.010.

Engemann DA, Gramfort A (2015): Automated model selection in covariance estimation and

spatial whitening of MEG and EEG signals. Neuroimage 108:328–342.

http://dx.doi.org/10.1016/j.neuroimage.2014.12.040.

Ernst MD (2004): Permutation methods: A basis for exact inference. Stat Sci 19:676–685.

Fischl B, Sereno MI, Tootell RBH, Dale a M (1999): High-resolution inter-subject averaging and a

surface-based coordinate system. Hum Brain Mapp 8:272–284.

Fischl B (2012): FreeSurfer. Neuroimage 62:774–781.

Fox MD, Snyder AZ, Vincent JL, Corbetta M, Van Essen DC, Raichle ME (2005): The human

brain is intrinsically organized into dynamic, anticorrelated functional networks. Proc Natl

Acad Sci U S A 102:9673–8.

http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=1157105&tool=pmcentrez&rende

rtype=abstract.

Frodl T, Hampel H, Juckel G, Bürger K, Padberg F, Engel RR, Möller HJ, Hegerl U (2002): Value

of event-related P300 subcomponents in the clinical diagnosis of mild cognitive impairment

and Alzheimer's disease. Psychophysiology 39:175–181.

Genovese CR, Lazar NA, Nichols T (2002): Thresholding of statistical maps in functional

neuroimaging using the false discovery rate. Neuroimage 15:870–878.

Goldenholz DM, Ahlfors SP, Hämäläinen MS, Sharon D, Ishitobi M, Vaina LM, Stufflebeam SM

(2009): Mapping the signal-to-noise-ratios of cortical sources in magnetoencephalography

and electroencephalography. Hum Brain Mapp 30:1077–1086.

Gramfort A, Luessi M, Larson E, Engemann DA, Strohmeier D, Brodbeck C, Goj R, Jas M,

Brooks T, Parkkonen L, Hämäläinen M (2013): MEG and EEG data analysis with MNE-

Python. Front Neurosci 7:1–13.

Halgren E, Baudena P, Clarke JM, Heit G, Liégeois C, Chauvel P, Musolino a (1995a):

Intracerebral potentials to rare target and distractor auditory and visual stimuli. I. Superior

temporal plane and parietal lobe. Electroencephalogr Clin Neurophysiol 94:191–220.

Halgren E, Baudena P, Clarke JM, Heit G, Marinkovic K, Devaux B, Vignal JP, Biraben a

(1995b): Intracerebral potentials to rare target and distractor auditory and visual stimuli. II.

Medial, lateral and posterior temporal lobe. Electroencephalogr Clin Neurophysiol 94:229–

250.

Halgren E, Squires NK, Wilson CL, Rohrbaugh JW, Babb TL (1980): Endogenous potentials

generated in the human hippocampal formation and amygdala by infrequent events.

Science (80-) 210:803–805.

Hämäläinen MS, Sarvas J (1989): Realistic conductivity geometry model of the human head for

interpretation of neuromagnetic data. IEEE Trans Biomed Eng 36:165–171.

http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&li

st_uids=2917762.

Hamilton HK, Boos AK, Mathalon DH (2020): Electroencephalography and Event-Related

Potential Biomarkers in Individuals at Clinical High Risk for Psychosis. Biol Psychiatry

88:294–303. https://doi.org/10.1016/j.biopsych.2020.04.002.

Hauk O, Wakeman DG, Henson R (2011): Comparison of noise-normalized minimum norm

estimates for MEG analysis using multiple resolution metrics. Neuroimage 54:1966–1974.

http://dx.doi.org/10.1016/j.neuroimage.2010.09.053.

Heilbronner SR, Platt ML (2013): Causal evidence of performance monitoring by neurons in

posterior cingulate cortex during learning. Neuron 80:1384–1391.

http://dx.doi.org/10.1016/j.neuron.2013.09.028.

Hill PF, Seger SE, Yoo H Bin, King DR, Wang DX, Lega BC, Rugg MD (2021): Distinct

neurophysiological correlates of the fMRI BOLD signal in the hippocampus and neocortex. J

Neurosci 41:6343–6352.

Hillyard SA, Squires KC, Bauer JW, Lindsay PH (1971): Evoked potential correlates of auditory

signal detection. Science 172:1357–1360.

http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&li

st_uids=5580218.

Hugdahl K, Raichle ME, Mitra A, Specht K (2015): On the existence of a generalized non-specific

task- dependent network. Front Hum Neurosci 9:1–15.

Hyvärinen A (1999): Fast and robust fixed-point algorithms for independent component analysis.

IEEE Trans Neural Networks 10:626–634.

Jas M, Engemann DA, Bekhti Y, Raimondo F, Gramfort A (2017): Autoreject: Automated artifact

rejection for MEG and EEG data. Neuroimage 159:417–429.

https://doi.org/10.1016/j.neuroimage.2017.06.030.

Johnson R (1988): Scalp-recorded p300 activity in patients following unilateral temporal

lobectomy. Brain 111:1517–1529.

Kim H (2014): Involvement of the dorsal and ventral attention networks in oddball stimulus

processing: A meta-analysis. Hum Brain Mapp 35:2265–84.

http://www.ncbi.nlm.nih.gov/pubmed/23900833.

Knight RT, Scabini D, Woods DL, Clayworth CC (1989): Contributions of temporal-parietal

junction to the human auditory P3. Brain Res 502:109–116.

Kobayashi Y, Amaral DG (2007): Macaque monkey retrosplenial cortex: III. cortical efferents. J

Comp Neurol 502:810–833.

Kretzschmar B, Gutschalk A (2010): A sustained deviance response evoked by the auditory

oddball paradigm. Clin Neurophysiol 121.

Larson E, Taulu S (2018): Reducing Sensor Noise in MEG and EEG Recordings Using

Oversampled Temporal Projection. IEEE Trans Biomed Eng 65:1002–1013.

Li F, Tao Q, Peng W, Zhang T, Si Y, Zhang Y, Yi C, Biswal B, Yao D, Xu P (2020): Inter-subject

P300 variability relates to the efficiency of brain networks reconfigured from resting- to task-

state: Evidence from a simultaneous event-related EEG-fMRI study. Neuroimage

205:116285. https://doi.org/10.1016/j.neuroimage.2019.116285.

Lin FH, Belliveau JW, Dale AM, Hamalainen MS (2006a): Distributed current estimates using

cortical orientation constraints. Hum Brain Mapp 27:1–13.

http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&li

st_uids=16082624.

Lin FH, Witzel T, Ahlfors SP, Stufflebeam SM, Belliveau JW, Hamalainen MS (2006b): Assessing

and improving the spatial accuracy in MEG source localization by depth-weighted minimum-

norm estimates. Neuroimage 31:160–171.

http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&li

st_uids=16520063.

Linden DE, Prvulovic D, Formisano E, Vollinger M, Zanella FE, Goebel R, Dierks T (1999): The

functional neuroanatomy of target detection: an fMRI study of visual and auditory oddball

tasks. Cereb Cortex 9:815–823.

http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&li

st_uids=10601000.

Logothetis NK, Pauls J, Augath M, Trinath T, Oeltermann a (2001): Neurophysiological

investigation of the basis of the fMRI signal. Nature 412:150–157.

http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&li

st_uids=11449264.

Maris E, Oostenveld R (2007): Nonparametric statistical testing of EEG- and MEG-data. J

Neurosci Methods 164:177–190.

Molins A, Stufflebeam SM, Brown EN, Hämäläinen MS (2008): Quantification of the benefit from

integrating MEG and EEG data in minimum ℓ2-norm estimation. Neuroimage 42:1069–1077.

Moores KA, Clark CR, Hadfield JLM, Brown GC, Taylor DJ, Fitzgibbon SP, Lewis AC, Weber DL,

Greenblatt R (2003): Investigating the generators of the scalp recorded visuo-verbal P300

using cortically constrained source localization. Hum Brain Mapp 18:53–77.

Mulert C, Pogarell O, Juckel G, Rujescu D, Giegling I, Rupp D, Mavrogiorgou P, Bussfeld P,

Gallinat J, Möller HJ, Hegerl U (2004a): The neural basis of the P300 potential: Focus on

the time-course of the underlying cortical generators. Eur Arch Psychiatry Clin Neurosci

254:190–198.

Mulert C, Jäger L, Schmitt R, Bussfeld P, Pogarell O, Möller HJ, Juckel G, Hegerl U (2004b):

Integration of fMRI and simultaneous EEG: Towards a comprehensive understanding of

localization and time-course of brain activity in target detection. Neuroimage 22:83–94.

Niessing J, Ebisch B, Schmidt KE, Niessing M, Singer W, Galuske R a W (2005): Hemodynamic

signals correlate tightly with synchronized gamma oscillations. Science (80-) 309:948–951.

http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&li

st_uids=16081740.

O'Connell RG, Dockree PM, Kelly SP (2012): A supramodal accumulation-to-bound signal that

determines perceptual decisions in humans. Nat Neurosci 15:1729–1735.

Onofrj M, Fulgente T, Nobilio D, Malatesta G, Bazzano S, Colamartino P, Gambi D (1992): P3

recordings in patients with bilateral temporal lobe lesions. Neurology 42:1762–1767.

Pascual-Marqui R D (2002): Standardized low resolution brain electromagnetic tomography

(sLORETA): technical details. Methods Find Exp Clin Pharmacol 24:5–12.

http://www.keyinst.unizh.ch/loreta.htm.

Peirce JW (2007): PsychoPy-Psychophysics software in Python. J Neurosci Methods 162:8–13.

http://dx.doi.org/10.1016/j.jneumeth.2006.11.017.

Polich J (2007): Updating P300: An integrative theory of P3a and P3b. Clin Neurophysiol

118:2128–2148.

Ritter W, Simson R, Vaughan HG (1972): Association cortex potentials and reaction time in

auditory discrimination. Electroencephalogr Clin Neurophysiol 33:547–555.

Rogers RL, Basile LFH, Papanicolaou AC, Eisenberg HM (1993): Magnetoencephalography

reveals two distinct sources associated with late positive evoked potentials during visual

oddball task. Cereb Cortex 3:163–169.

Sekihara K, Nagarajan SS (2008): Adaptive Spatial Filters for Electromagnetic Brain Imaging.

Series in. Springer, Berlin; Heidelberg.

Sergent C, Baillet S, Dehaene S (2005): Timing of the brain events underlying access to

consciousness during the attentional blink. Nat Neurosci 8:1391–1400.

Siedenberg R, Goodin DS, Aminoff MJ, Rowley HA, Roberts TPL (1996): Comparison of late

components in simultaneously recorded event-related electrical potentials and event-related

magnetic fields. Electroencephalogr Clin Neurophysiol 99:191–197.

Squires NK, Squires KC, Hillyard SA (1975): Two varieties of long-latency positive waves evoked

by unpredictable auditory stimuli in man. Electroencephalogr Clin Neurophysiol 38:387–401.

http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=PubMed&dopt=Citation&li

st_uids=46819.

Steinmann I, Gutschalk A (2011): Potential fMRI correlates of 40-Hz phase locking in primary

auditory cortex, thalamus and midbrain. Neuroimage 54:495–504.

http://www.ncbi.nlm.nih.gov/pubmed/20688174.

Strom A, Iaccarino L, Edwards L, Lesman-Segev OH, Soleimani-Meigooni DN, Pham J, Baker

SL, Landau SM, Jagust WJ, Miller BL, Rosen HJ, Gorno-Tempini ML, Rabinovici GD, La

Joie R (2022): Cortical hypometabolism reflects local atrophy and tau pathology in

symptomatic Alzheimer's disease. Brain 145:713–728.

Sutton S, Braren M, Zubin J, E. R. John (1965): Evoked-Potential Correlates of Stimulus

Uncertainty. Science (80-) 150:1187–8.

Tarkka IM, Stokić DS, Basile LF, Papanicolaou a C (1995): Electric source localization of the

auditory P300 agrees with magnetic source localization. Electroencephalogr Clin

Neurophysiol 96:538–545.

Twomey DM, Murphy PR, Kelly SP, O'Connell RG (2015): The classic P300 encodes a build-to-

threshold decision variable. Eur J Neurosci 42:1636–43.

http://www.ncbi.nlm.nih.gov/pubmed/25925534.

Uutela K, Taulu S, Hämäläinen M (2001): Detecting and correcting for head movements in

neuromagnetic measurements. Neuroimage 14:1424–1431.

Verleger R, Heide W, Butt C, Kömpf D (1994): Reduction of P3b in patients with temporo-parietal

lesions. Brain Res Cogn Brain Res 2:103–116.

Verleger R (2020): Effects of relevance and response frequency on P3b amplitudes: Review of

findings and comparison of hypotheses about the process reflected by P3b.

Psychophysiology 57:1–22.

Verleger R, Metzner MF, Ouyang G, Śmigasiewicz K, Zhou C (2014): Testing the stimulus-to-

response bridging function of the oddball-P3 by delayed response signals and residue

iteration decomposition (RIDE). Neuroimage 100:271–280.

Vogt BA (2019): The cingulate cortex in neurologic diseases: History, Structure, Overview.

Handbook of Clinical Neurology 1st ed. Elsevier B.V. Vol. 166.

http://dx.doi.org/10.1016/B978-0-444-64196-0.00001-7.

Vogt BA, Nimchinsky EA, Vogt LJ, Hof PR (1995): Human cingulate cortex: Surface features, flat

maps, and cytoarchitecture. J Comp Neurol 359:490–506.

Vogt BA, Pandya DN (1987): Cingulate cortex of the rhesus monkey: II. Cortical afferents. J

Comp Neurol 262:271–289.

Yamaguchi S, Knight RT (1991): Anterior and posterior association cortex contributions to the

somatosensory P300. J Neurosci 11:2039–2054.

Yeo BTT, Krienen FM, Sepulcre J, Sabuncu MR, Lashkari D, Hollinshead M, Roffman JL, Smoller

JW, Zöllei L, Polimeni JR, Fisch B, Liu H, Buckner RL (2011): The organization of the

human cerebral cortex estimated by intrinsic functional connectivity. J Neurophysiol

106:1125–1165.

Ziontz J, Adams JN, Harrison TM, Baker SL, Jagust WJ (2021): Hippocampal connectivity with

retrosplenial cortex drives neocortical tau accumulation and memory function. J Neurosci

41:8839–8847.

Supporting information

A role for retro-splenial cortex in the task-related P3 network

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Figure S1 Cortical M/EEG and fMRI activation maps. These maps represent combined M/EEG source estimates similar to those shown in Figure 2a, but with alternative source analysis methods, using (a) sLORETA and (b) a Borgiotti-Kaplan beamformer. Note that the numerical values cannot be directly compared between these source estimation methods, even though they represent noise normalized z-scores.

Figure S2 fMRI maps for the contrast deviants – standards, based on a random-effects statistic.

Same analysis as Figure 2c but with more conservative cutoff (p<0.01, FDR corrected).

Figure S3 Point spread analysis table based on the M/EEG data. The spread values range from

0 (minimum) to 1 (maximum).

Figure S4 Cross-talk analysis table based on the M/EEG data. The cross-talk values range from

0 (minimum) to 1 (maximum).

Figure S5 EEG and MEG maps for individual participants. The responses are mapped at the individual peak latency for N1 (left) stimulus-locked P3b (middle), and response-locked P3b (right) for individual participants 1 - 6.

Figure S6 EEG and MEG maps for individual participants. The responses are mapped at the

individual peak latency for N1 (left) stimulus-locked P3b (middle), and response-locked P3b (right)

for individual participants 7 - 12.

Figure S7 Simulated M/EEG for a distributed superior parietal cortex (SPC) and a temporo-

parietal junction source (TPJ) source. (a) dSPM analysis for simulated distributed SPC (left) and

TPJ (right) sources (n=12 subjects; p<0.01). (b) Average EEG and MEG maps for the simulated

distributed SPC (left) and TPJ (right) sources.

914 **Table S1** Modeling the grand-average N1 pattern with simulated M/EEG based on anatomically

915 defined source regions (Figure 4b).

	Simulated source activation patterns					Residual variance (RV) (%)	
	AC	Insula	S1	RSC	aMCC	EEG	MEG
Source strength (nAm)	27.75	9.25	0.0	0.0	0.0	16.25	27.80
	28.75	-	-	-	-	20.70	26.80
	-	26.50	-	-	-	69.60	100.0

917 **Table S2** Modeling the grand-average P3b pattern with simulated M/EEG based on anatomically

918 defined source regions (Figure 4b). In this simulation, the extended superior parietal source (SPC;

919 see Figure S6) is used instead of the retro-splenial cortex (RSC).

	Simulated source activation patterns					Residual variance (RV) (%)	
	AC	**Insula**	**S1**	**SPC**	**aMCC**	**EEG**	**MEG**
	5.0	11.25	10.0	69.50	0.	8.90	66.60
Source strength (nAm)	-	7.25	11.75	66.25	6.50	8.80	70.30
	3.0	-	11.25	64.0	6.25	8.0	73.40
	9.0	16.0	-	79.0	0.	11.10	75.10
	0.	0.	22.75	-	4.0	52.90	87.10
	5.0	11.25	10.0	69.50	-	8.90	66.60