

## Full Length Articles

## Multiple brain networks underpinning word learning from fluent speech revealed by independent component analysis



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## ABSTRACT

Although neuroimaging studies using standard subtraction-based analysis from functional magnetic resonance imaging (fMRI) have suggested that frontal and temporal regions are involved in word learning from fluent speech, the possible contribution of different brain networks during this type of learning is still largely unknown. Indeed, univariate fMRI analyses cannot identify the full extent of distributed networks that are engaged by a complex task such as word learning. Here we used Independent Component Analysis (ICA) to characterize the different brain networks subserving word learning from an artificial language speech stream. Results were replicated in a second cohort of participants with a different linguistic background. Four spatially independent networks were associated with the task in both cohorts: (i) a dorsal Auditory-Premotor network; (ii) a dorsal Sensory-Motor network; (iii) a dorsal Fronto-Parietal network; and (iv) a ventral Fronto-Temporal network. The level of engagement of these networks varied through the learning period with only the dorsal Auditory-Premotor network being engaged across all blocks. In addition, the connectivity strength of this network in the second block of the learning phase correlated with the individual variability in word learning performance. These findings suggest that: (i) word learning relies on segregated connectivity patterns involving dorsal and ventral networks; and (ii) specifically, the dorsal auditory-premotor network connectivity strength is directly correlated with word learning performance.

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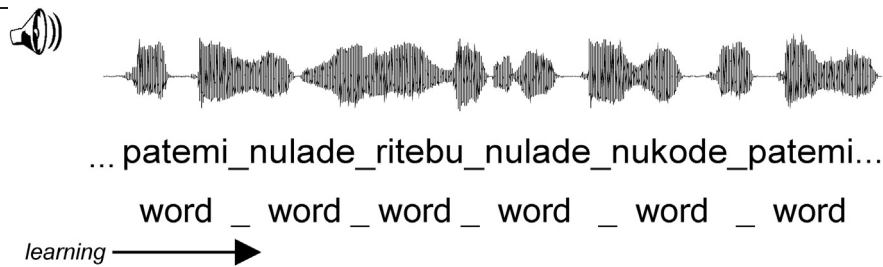
Despite the apparent ease with which humans speak and communicate, learning a new language is a complex task that everyone needs to face at least once in her or his lifetime. A central aspect of this process is the acquisition of new words. In natural circumstances, learners need to first discover word units from fluent speech. This process may rely on statistic-based mechanisms which track regularities between phonemes and syllables, as well as on the detection of the subtle prosodic cues that can help word segmentation (e. g. pauses, intonation, etc.; Aslin et al., 1998; Peña et al., 2002). Then, memory traces of those isolated word forms need to be progressively enhanced through

subsequent encounters (Saffran, 2001) in order to be memorized and stored in long-term memory (for a review: Rodriguez-Fornells et al., 2009).

Therefore, as shown for other complex cognitive functions, new word learning may rely on widespread segregated and overlapping large-scale networks (Mesulam, 1990), even before meaning is attached to them. Interestingly, we have recently shown that the ability to learn novel word forms is related to functional and structural connectivity between the auditory cortical area (comprising the superior temporal gyrus, STG) and the motor regions (comprising the premotor cortex, PMC; and the inferior frontal gyrus, IFG) through the direct connection of the arcuate fasciculus in the left hemisphere (López-Barroso et al., 2013). These regions belong to the dorsal stream of language processing, which is in charge of mapping sound into articulation (Hickok and Poeppel, 2000; Hickok et al., 2011; Rauschecker and Scott, 2009; Saur et al., 2008), a process that might be involved in the acquisition of

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**Fig. 1.** Schematic illustration of the artificial language stream used in the learning phase of the experiments. The stream was aurally presented and it was composed of nonsense trisyllabic words that were repeated across the stream. The “\_” represent the 25 millisecond pause inserted between the words in order to mark word boundaries.

new vocabulary (Hickok and Poeppel, 2007; Rodriguez-Fornells et al., 2009). At the same time, the areas of the dorsal stream along with the inferior parietal lobe (Buchsbaum and D’Esposito, 2008; Corbetta and Shulman, 2002) are related to the rehearsal and attentional mechanisms necessary to maintain phonological information in working memory (Jacquemot and Scott, 2006); a function that is likely to be required to keep the phonological form of the segmented word in an active state in order to be memorized.

Thus far, previous reports of functional neuroimaging of the very first stages of word learning are limited (Cunillera et al., 2009; Karuza et al., 2013; McNealy et al., 2006, 2011). In spite of some methodological differences, all of these studies required participants to listen to a continuous flow of speech composed of nonsense trisyllabic words with no meaning attached. McNealy et al. (2006) identified increased activity in the left inferior and middle frontal gyrus when comparing words (presented during the learning phase) with partwords as the neural signature of on-line word learning. In addition, during learning, temporal and parietal regions showed increased activity when listening to a stream containing words compared to a stream containing syllables in random order. Cunillera et al. (2009) also reported the involvement of the PMC during the initial stages of the learning process. Finally, a recent study reported a correlation between IFG activation and segmentation abilities (Karuza et al., 2013). Although the univariate analysis approach taken by these studies allows only spotting the involvement of a variety of independent regions, the regions highlighted suggest an involvement of the dorsal stream in word learning. However, to date there is no information about how these segregated regions functionally interact during word learning.

Here we used independent component analysis (ICA) to identify the whole set of functional networks engaged during a word-learning task, when no meaning is attached to the new words. ICA is a data-driven approach (Calhoun et al., 2008) that allows the measurement of both the BOLD response fluctuations in the active and the spontaneous fluctuations in the resting brain (Smith et al., 2009). It captures the integrated activity of spatially distributed brain regions (i.e. functional integration; Friston, 2011; Smith, 2012) without any a priori constraint. ICA is especially well-suited to discern how multiple functional networks – subserving different cognitive processes – synergistically interact (Calhoun et al., 2001; Celone et al., 2006; Wu et al., 2009). ICA presents some advantages over univariate analysis, as for example, it does not need a temporal model of brain functioning. Univariate analysis provides optimal results when the activated areas follow an almost canonical BOLD response, but in contrast, is blind to other types of changes (for example transient task-related, non-task related, slow varying changes, etc., Calhoun et al., 2009; McKeown et al., 1998). Moreover, recent studies have shown that different neural circuits can occur concurrently within the same brain areas, but cannot be resolved by standard GLM analysis (Beldzik et al., 2013; Xu et al., 2013a,b).

In this study, participants completed an artificial word-learning task which tapped the initial stages of word learning, when auditory

word forms need to be learned from fluent speech and no meaning is yet associated to them (De Diego-Balaguer et al., 2007; Peña et al., 2002). First, we aimed to define the brain networks that were engaged and disengaged during the word-learning task. As the ICA analysis is fully data-driven, similar experiments were performed in two different cohorts of participants with different linguistic backgrounds (Spanish [ $n = 25$ ] and German [ $n = 16$ ]), searching for replication (Bennet et al., 2009; Button et al., 2013; Lieberman and Cunningham, 2009). Second, we aimed to study which of the engaged networks was associated with the individual variability in the word learning performance.

## Material and methods

### Participants

Forty-three participants were recruited for the study. Twenty-seven native Spanish speakers (mean age: 24.7, SD: 4.6, 12 women) were involved in the main cohort, while the replication cohort involved sixteen German speakers (mean age, 26.6; SD: 4.6, 8 women). Written consent was obtained from all subjects and they were paid for their participation. They all were free of neurological and otological diseases. Experiments were approved by the respective local ethical committees.

### Artificial word-learning task

#### Main cohort

The experiment involved a learning and a test phase. During the learning phase, subjects conducted an artificial word-learning task (Fig. 1) administered in two runs. Eight different artificial languages were used, including six that had been employed in a previous study (De Diego-Balaguer et al., 2007) and two new languages that were validated in a behavioral pilot study. Stimuli were presented through MR-compatible headphones. Each participant heard two of the eight languages created, one in each run. The order of the languages was counterbalanced among subjects. Streams and test items were built using MBROLA speech synthesizer software (Dutoit et al., 1996). The languages were built by concatenating nine different trisyllabic nonsense words (De Diego-Balaguer et al., 2007; Peña et al., 2002; Saffran et al., 1996) that followed Spanish phonotactic constraints. Words had a duration of 696 ms each, and subtle pauses of 25 ms were inserted between them in order to introduce a prosodic cue to enhance the segmentation process (Fig. 1). During the task, 4 active blocks, each including 42-word presentations (30 s), were alternated with resting blocks of 20 s duration. Words were presented in the form of a fluent speech stream and concatenated pseudo-randomly such that the same word was never immediately repeated in the stream. Participants were told to pay attention to the nonsense language stream, as later on they would be asked about the “words” presented within the streams.

After the language exposure in each run, word learning was assessed behaviorally by testing words that had been presented during the

learning phase and words that had not been presented (“non-words”). Non-words were built with the same syllables as the words presented in the learning phase, but in an incorrect order. Responses were recorded using an MR-compatible response box containing two response buttons (forefinger and middle-finger of the left hand). Participants heard a word or non-word presented in isolation and they were required to press with the middle finger button if they thought the stimulus was a word of the learned language and with the index finger if they thought that it was a non-word. The experiment was presented using the Presentation Software. In order to assess participants' ability to correctly discriminate words from non-words, their behavioral responses were transformed into d-prime scores (MacMillan and Creelman, 2005). The subjects' overall performance indicated that words of the languages were indeed learned (behavioral data for two subjects was not available due to technical problems in the recording): participants reliably distinguished between words and non-words ( $t(24) = 2.74, p < 0.01$ ).

#### Second cohort

For the second cohort, given that participants were native German speakers, the materials were modified to use German phonemes. This was done by applying the German diphone database from the MBROLA text-to-speech synthesizer. Speech streams preserved German phonotactics. The same procedure as for the main cohort was used for the learning and test phases except that, in order to have a greater signal-to-noise relation, 3 runs with 6 language-rest blocks per run were used. The duration of each active and resting block was the same as for the main cohort. Although responses could not be recorded in this scanner, to maintain the same procedure as in the main cohort, participants were required to respond during the test phase in the same manner as the participants from the first cohort. The materials used were tested in another group of participants ( $N = 13$ ) and confirmed that learning was also possible with the modified version of the material ( $t(12) = 4.27, p < 0.001$ ).

#### Image acquisition

##### Main cohort

Images were acquired using a 3.0 T Siemens Trio MRI system at the Hospital Clinic of Barcelona. Functional images were obtained using a single-shot  $T_2^*$ -weighted gradient-echo EPI sequence (slice thickness = 4 mm; no gap; number of slices = 32, order of acquisition interleaved; repetition time (TR) = 2000 ms; echo time (TE) = 29 ms; flip angle =  $80^\circ$ ; matrix =  $128 \times 128$ ; field of view FOV = 240 mm; voxel size =  $1.87 \times 1.87 \times 4 \text{ mm}^3$ ). Each slice was aligned to the plane intersecting the anterior and posterior commissures. In addition to the functional runs a high-resolution  $T_1$ -weighted image (slice thickness = 1 mm; no gap; number of slices = 240; repetition time (TR) = 2300 ms; echo time (TE) = 3 ms; matrix =  $256 \times 256$ ; field of view (FOV) = 244 mm) was also acquired for each subject.

##### Replication cohort

Images were acquired using a 3.0 T Siemens Allegra MRI system at International Neuroscience Institute in Hannover, Germany. Functional images were obtained using a single-shot  $T_2^*$ -weighted gradient-echo EPI sequence [slice thickness = 3 mm; distance factor = 25% (0.7 mm); number of slices = 34, order of acquisition interleaved; repetition time (TR) = 2000 ms; echo time (TE) = 30 ms; flip angle =  $80^\circ$ ; matrix =  $128 \times 128$ ; FOV = 192 mm; voxel size =  $3 \times 3 \times 3 \text{ mm}^3$ ]. Each slice was aligned to the plane intersecting the anterior and posterior commissures. In addition to the functional runs a high-resolution  $T_1$ -weighted image [slice thickness = 1 mm; no gap; number of slices = 192; repetition time (TR) = 15 ms; echo time (TE) = 4.9 ms; matrix =  $256 \times 256$ ; FOV = 256 mm] was also acquired for each subject.

#### Preprocessing and ICA analysis

In both cohorts, the ICA analysis was performed on the fMRI data acquired during the learning phase. Data were preprocessed using Statistical Parameter Mapping software (SPM8, Wellcome Department of Imaging Neuroscience, University College, London, UK, [www.fil.ion.ucl.ac.uk/spm/](http://www.fil.ion.ucl.ac.uk/spm/)). For the main cohort, the two functional runs were realigned and their mean image was calculated. The structural  $T_1$ s were co-registered to their respective mean functional image and segmented using the New Segment toolbox included in SPM8. Following segmentation, gray and white matter images were fed to DARTEL (Ashburner, 2007) in order to achieve normalization. After normalization, data was subsampled to  $1.5 \times 1.5 \times 1.5 \text{ mm}^3$  ( $121 \times 145 \times 121$  voxels) and spatially smoothed with an  $8 \times 8 \times 8$  full width at half maximum (FWHM) Gaussian kernel. For the replication cohort, the three functional runs were also realigned and a mean image of all the EPIs was created. After an initial 12-parameter affine transformation of this mean to the EPI MNI template, the resulting normalization parameters derived were applied to the whole functional set. Finally, functional EPI volumes were re-sampled into  $4 \times 4 \times 4 \text{ mm}$  voxels and spatially smoothed with an 8 mm FWHM kernel.

Group Spatial ICA was used to extract the different networks present during each of the experiments using the GIFT software (<http://icatb.sourceforge.net/>). ICA was applied with the number of independent components set to 20, which has been shown to be an optimal dimension in previous studies (Forn et al., 2013; Smith et al., 2009). Following this, the functional images from each of the cohorts were analyzed using group ICA, which started with an intensity normalization step. After this first step, data was first concatenated and then reduced to 20 temporal dimensions (using principal component analysis), to be then analyzed with the infomax algorithm (Bell and Sejnowski, 1995). No scaling was used, as with the intensity normalization step, the intensities of the spatial maps obtained are already in percentage of signal change.

A one-sample  $t$ -test was calculated using the individual spatial maps, which treats each subject's network as a random effect (Calhoun et al., 2001). All networks (see Fig. 2) are shown at  $p < 0.01$  corrected threshold using the false discovery rate (FDR) algorithm with a cluster extent of 30 voxels. FDR correction has been widely used to report ICA components (Calhoun et al., 2001, 2008; Eichele et al., 2008; Forn et al., 2013; Wu et al., 2009).

#### Calculation of task-related networks

In order to identify which of the networks retrieved were related to the task (i. e., word learning from fluent speech), a multiple regression was calculated using GIFT. This allows fitting each subject's component time course to the model. Models were created using SPM8 by convolving a canonical hemodynamic response with the timing of the active and resting blocks of the learning phase. First, all networks were visually inspected in order to detect artifactual components reflecting movements, ventricles, edges or the presence of blood vessels. Eight networks from the main cohort and 6 from the replication cohort were discarded. Then, for the remaining networks (12 for the first and 14 for the second cohort), a model including only two conditions was created: learning from fluent speech (active blocks) and rest. For each of the remaining networks, a one-sample  $t$ -test was performed on all the beta values obtained from the learning condition regressor. A network was considered task-related if the regressor survived the fit ( $p < 0.05$ , uncorrected for multiple comparisons; Calhoun et al., 2008; Forn et al., 2013; see Fig. 2 and Tables 3 and 4). The analysis of the task-relatedness of the networks extracted for the second cohort was done specifically to replicate the results obtained in the main cohort. Independent replication is crucial to differentiate true effects from random noise and to firmly establish a result (Bennet et al., 2009; Button et al., 2013). It also minimizes Type I errors, as false positives are not likely to replicate across different studies (Lieberman and Cunningham, 2009). At the same time it allows

avoiding committing Type II errors that may rise from a too restrictive Bonferroni correction. Replicating the same networks in two different cohorts of individuals with different language backgrounds, with MRI data being collected in different scanners, and also using two different sets of stimuli (one following the phonotactic rules of Spanish and the other of German) proves that the reported networks do not come from spurious correlations. In agreement with this, here we focused our discussion on the networks that were significantly engaged during both the main and the replication cohorts. In addition, and in order to provide the reader with all the information, we indicate which of these networks survived the correction for multiple comparisons. Note that our strongest claims are therefore limited to these networks. Tables 1, 2 and 4 show which of the task-related networks survived a Bonferroni correction for multiple comparisons:  $p$ -values under 0.0041 for the first cohort (12 networks were tested), under 0.0035 for the second (14 networks tested).

#### Relationship between network engagement and learning performance

Once the networks significantly engaged during word learning were established, a second fine-grained task-related analysis was performed. The aim was to relate each task-related network with learning performance over time. For this, we calculated a new model defining 5 conditions: learning during block 1, 2, 3 and 4, and rest. This analysis was only performed for the main cohort, as behavioral responses inside the scanner were not available for the replication cohort. Therefore, an independent beta value for each of the four blocks comprising the task (two repetitions per condition in each of the two runs) was extracted for the 5 task-related networks replicated in both cohorts. Once again, a one-sample  $t$ -test was carried out on all the beta values for the active task regressor of each block ( $p < 0.05$ , uncorrected for multiple comparisons). The networks surviving the correction for multiple comparisons are indicated in Table 5 ( $p$ -values under 0.0025, as four blocks were tested for 5 networks). As no replication here was possible, only the networks surviving multiple comparisons correction were further analyzed. Therefore, correlations were calculated between word learning performance ( $d$  prime) and each participant's beta value only for those blocks and networks. In addition, correlations were performed using the Robust Correlation Toolbox (Pernet et al., 2013) to compute Pearson skipped correlations (Rousseeuw and Van Driessen, 1999; Rousseeuw, 1984; Verboten and Hubert, 2005) which involve multivariate outlier detection and can provide a more robust measure of correlation (Rousseeuw and Pernet, 2012). In this last analysis, which was done to confirm a direct relationship with learning performance, no correction for multiple comparisons was applied (6 correlations were calculated: first block, dAPMN and dSMN; second block, dAPMN; third block, dAPMN; fourth block, dAPMN and dSMN; see Results section).

## Results

### ICA decomposition

#### Main cohort

Three out of the remaining 12 ICA networks (after removal of those corresponding to artifacts) were significantly positively correlated to the word-learning task (see Table 1 for statistical values) with a fourth one being marginally related ( $p = 0.052$ ). These same three networks

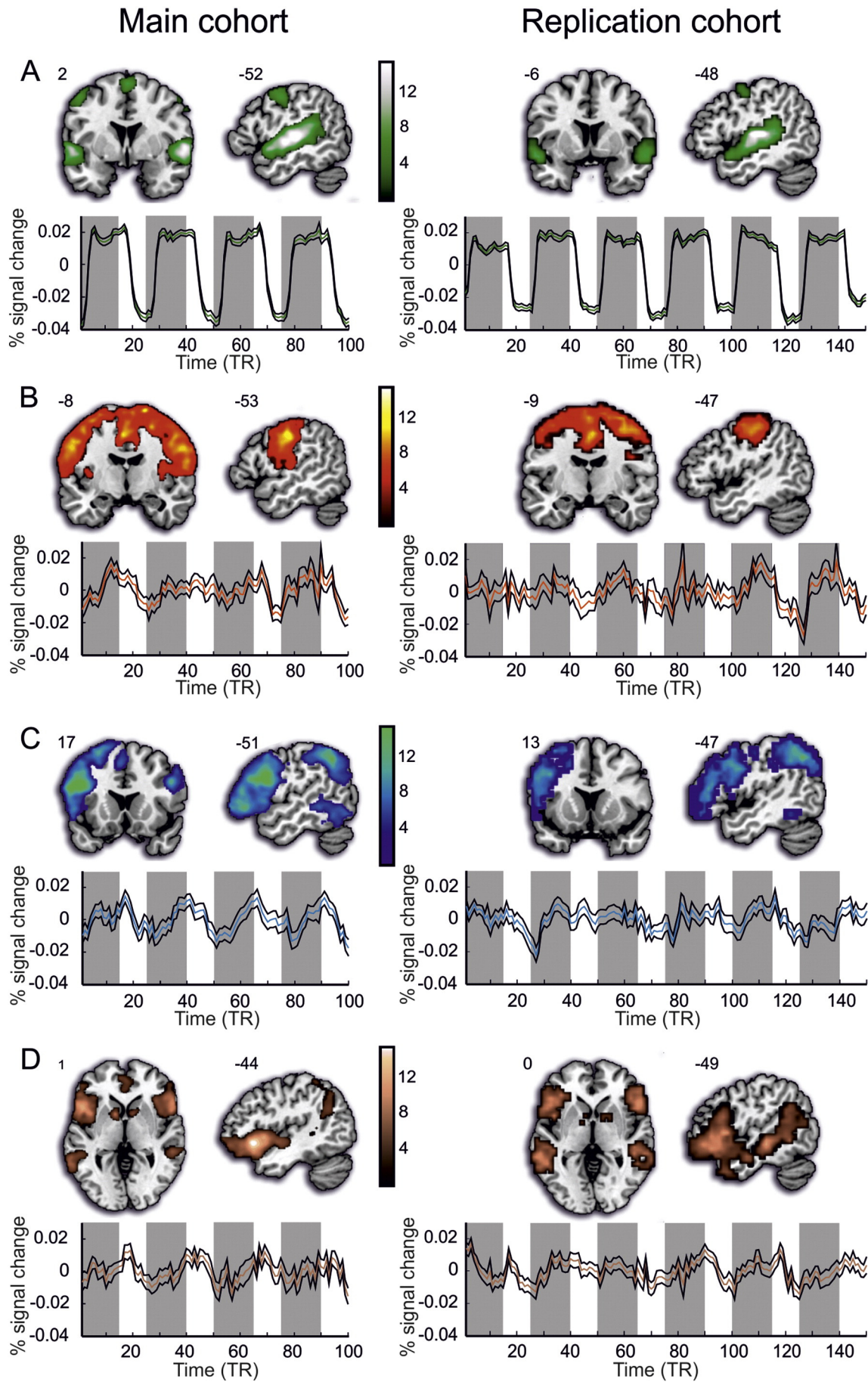
were also retrieved as task-related in the replication cohort (see below). From those, only two out of three networks survived the correction for multiple comparisons (dorsal Auditory-Premotor Network and dorsal Sensory-Motor Network; Table 1). The task-related ICA maps (networks) are displayed in Fig. 2 (left panels) along with their respective BOLD time courses. Three of these networks were considered “dorsal” networks (Table 1): a dorsal Auditory-Premotor Network (dAPMN, Fig. 2A) covering the bilateral superior temporal gyrus (STG) and superior temporal sulcus (STS) extending to the dorsal part of the middle temporal gyrus (MTG), the Sylvian Parietal Temporal area (SPT), the premotor cortex (PMC), the supplementary motor area (SMA) and pre-SMA; a dorsal Sensory-Motor Network (dSMN, Fig. 2B) comprising the pre- and post-central gyri, PMC and SMA; and a left lateralized dorsal Fronto-Parietal Network (dFPN, Fig. 2C) covering mainly frontal (including the inferior [IFG] and middle [MFG] frontal gyrus) and parietal (both inferior and superior) areas. The fourth network, marginally related to the task, was identified as a ventral Fronto-Temporal Network (vFTN, Fig. 2D), covering the prefrontal and insular cortex, the anterior superior and middle temporal cortex and the caudate nucleus. Finally, the Default Mode Network (DMN, Fig. 3A) was the only network significantly negatively correlated with the task. The DMN comprised its typical constituents, i.e. bilateral parietal and occipital gyri, the precuneus, posterior and middle cingulate gyri, the superior middle frontal and the anterior cingulate gyri.

The remaining 7 networks that did not pass the threshold to be considered related to the task ( $p < 0.05$ ) were labeled as: Superior Parietal, Lateral Visual, Cerebellar, Medial Visual, Cingulate, Mesial Temporal and right Fronto-Parietal (see Table 3). All of these networks have been previously identified and reported both during active task and resting state paradigms (Forn et al., 2013; Smith et al., 2009; Tie et al., 2008).

#### Replication cohort

Six out of the 14 ICA remaining networks (after removal of those corresponding to artifacts) were significantly positively correlated to the word-learning task (see Table 2 for statistical values). The three task-related networks identified in the main cohort (dAPMN, dSMN, dFPN) were among those six networks. In addition, it is worth mentioning that the fourth network, the vFTN, passed the significance threshold ( $p < 0.045$ , see Table 2 and Fig. 2D, right panel) while in the main cohort this network resulted marginally related ( $p = 0.052$ ). Importantly, the areas belonging to these networks were highly consistent compared with the ones belonging to the networks from the main cohort (see Fig. 2, left panel). As in the main cohort, the engagement of the dAPMN and dSMN survived multiple comparison correction. The two other networks that correlated with the model were an Insular Network comprising the insula bilaterally and the SMA; and a Lateral Visual Network covering the lateral aspects of bilateral superior, middle and inferior occipital and fusiform gyri (Table 2). The latter network was retrieved also in the main cohort. However, it was not significantly or marginally related to the task (see Table 3 for statistical values). Again, the DMN was the only network significantly negatively correlated with the task (see Fig. 3B). The remaining 7 networks that did not pass the threshold to be considered related to the task ( $p < 0.05$ ) were very similar to those that did not reach the threshold either in the main cohort. These networks have also been previously reported both in task-related and resting state ICA studies (Forn et al., 2013; Smith et al., 2009; Tie et al., 2008) and were labelled as Medial Visual, Medial

**Fig. 2.** Task-related networks and associated hemodynamic time courses for the main cohort (left panel) and the replication cohort (right panel). Three of the networks were identified as dorsal networks: dorsal Auditory-Premotor (A); dorsal Sensory-Motor (B); and dorsal Fronto-Parietal (C). The fourth network was identified as a ventral Fronto-Temporal network (D). Each component is rendered onto the MNI template at representative slices, with MNI coordinates in millimeters shown in the top left corners. Components are shown with a cluster extent of 30 voxels with a 1% false discovery rate with the threshold bar shown at the right side of each panel. On the lower part of each panel, the associated time course for each component is shown. The mean time course over the 27 subjects (main cohort) and the 16 subjects (replication cohort) is shown in a central, colored line with standard error of the mean depicted with black lines. Only left hemisphere is shown in the sagittal views.



**Table 1**

Different task-related ICA networks with their respective areas of activation and their statistical level of task relatedness for the main cohort of participants (n = 27). TRN: task-related network; BA: Brodmann areas; dAPMN: dorsal auditory-premotor network; dSMN: dorsal sensory-motor network; dFPN: dorsal fronto-parietal network; vFTN: ventral fronto-temporal network; DMN: default mode network. \* Survived the correction for multiple comparisons.

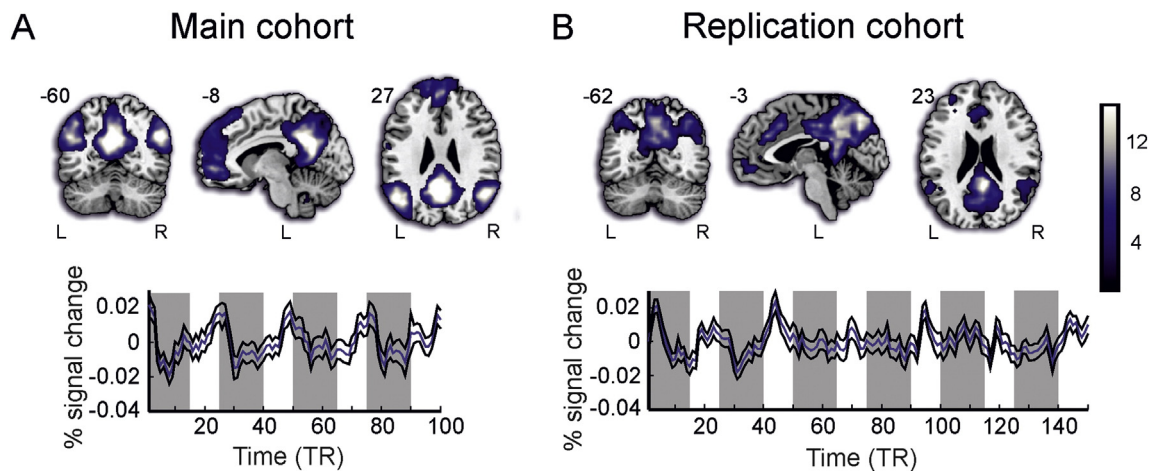
TRN	Activation region	BA	Task relatedness T-val (p-val)
dAPMN Fig. 2A	Bilateral sup/mid temporal gyrus; bilateral heschl gyrus; bilateral insula; bilateral precentral gyrus; left postcentral gyrus; supplementary motor area; pre-supplementary motor area	22, 21, 13, 41, 42, 6, 4	15.20 (0.001)*
dSMN Fig. 2B	Bilateral precentral gyrus; bilateral postcentral gyrus; supplementary motor area; pre-supplementary motor area; bilateral middle cingulate gyrus	4, 3, 6, 2, 24	3.77 (0.001)*
dFPN Fig. 2C	Left sup/inf temporal gyrus; bilateral middle temporal gyrus; bilateral angular gyrus; left supramarginal gyrus; bilateral superior occipital gyrus; left inf/mid occipital gyrus; bilateral inf/sup parietal gyrus; left precuneus; bilateral inferior frontal gyrus orb/trian/oper; bilateral middle frontal gyrus; left superior frontal gyrus; supplementary motor area; bilateral precentral gyrus	44, 45, 46, 47, 21, 22, 20, 19, 37, 39, 40, 7, 89, 10, 11, 6	2.12 (0.043)
vFTN Fig. 2D	Bilateral insula; bilateral temporal pole; bilateral inf. frontal gyrus pars triang/oper/orb; bilateral anterior cingulate gyrus; bilateral frontal superior medial gyrus; bilateral caudate head; left globus pallidum; bilateral mid/sup temporal gyrus; bilateral supramarginal gyrus; bilateral angular gyrus; bilateral inferior parietal gyrus	47, 45, 44, 38, 22, 13, 40, 10, 9, 32	2.03 (0.052)
DMN Fig. 3A	Bilateral cuneus; bilateral precuneus; bilateral middle occipital gyrus; bilateral inferior parietal gyrus; bilateral angular gyrus; bilateral middle temporal; bilateral ant/post/mid cingulate gyrus; bilateral sup/mid frontal gyrus;	40, 39, 7, 22, 19, 31, 29, 5, 238, 9, 10, 11, 32	-2.58 (0.015)

**Table 2**

Different task-related ICA networks with their respective areas of activation and their statistical level of task relatedness from the replication cohort (n = 16). TRN: task-related network; BA: Brodmann areas; dAPMN: dorsal auditory-premotor network; dSMN: dorsal sensory-motor network; dFPN: dorsal fronto-parietal network; vFTN: ventral fronto-temporal network; DMN: default mode network; VLN: visual lateral network; IN: insular network.

TRN	Activation region	BA	Task relatedness T-val (p-val)
dAPMN Fig. 2A	Bilateral sup/mid temporal gyri; bilateral heschl gyri; bilateral insula; left precentral gyrus; left postcentral gyrus.	22,21,13,41,42,6,4	18.00 (0.001) <sup>a</sup>
dSMN Fig. 2B	Bilateral precentral gyri; bilateral postcentral gyri; supplementary motor area; pre-supplementary motor area; bilateral middle cingulate gyri; bilateral thalamus; bilateral caudate.	4,3,6,2,24	4.73 (0.001) <sup>a</sup>
dFPN Fig. 2C	Left inf/mid temporal gyrus; bilateral angular gyri; left supramarginal gyrus; bilateral superior occipital gyri; left inf/mid occipital gyrus; bilateral inf/sup parietal gyri; left precuneus; left inferior frontal gyrus orb/trian/oper; bilateral middle frontal gyri; left superior frontal gyrus; supplementary motor area; left precentral gyri; left hippocampus.	44,45,46,47,21,22,20,19,37,39,40,7,8,9,10,11,6	3.30 (0.004)
vFTN Fig. 2D	Bilateral insula; bilateral temporal pole; bilateral inf. frontal gyri pars trian/oper/orb; supplementary motor area; bilateral frontal superior medial gyri; bilateral caudate head; bilateral globus pallidum; bilateral middle/superior temporal gyri; bilateral supramarginal gyri; bilateral angular gyri.	47,45,44,38,22,21,13,40,89	2.19 (0.045)
DMN Fig. 3B	Bilateral cuneus; bilateral precuneus; bilateral superior/middle occipital gyrus; bilateral anterior/posterior/middle cingulate gyrus; bilateral angular gyrus; bilateral sup/infr parietal gyrus; right middle temporal.	7,31,23,32,40,19,39	-3.13 (0.007)
VLN Fig. S1A	Bilateral mid./sup./inf. occipital gyri; bilateral sup/inf. parietal gyri; bilateral fusiform gyri; bilateral mid/inf temporal; bilateral postcentral gyri; bilateral cuneus; bilateral lingual gyrus; bilateral middle frontal	19,18,7,37,40,10	2.31 (0.035)
IN Fig. S1B	Bilateral insula; bilateral precentral gyri; bilateral postcentral gyri; supplementary motor area; cuneus.	6,31,13	3.95 (0.0015) <sup>a</sup>

<sup>a</sup> Survived the correction for multiple comparisons.



**Fig. 3.** The default mode network, which resulted anticorrelated with the task in the main (A) and the replication (B) cohorts, is rendered onto the MNI template at representative coronal, sagittal and axial slices with MNI coordinates in millimeters shown in the top left corners. The average time course over the 27 subjects in the main cohort and over the 16 subjects in replication cohort (blue line), and the standard error of the mean (black lines) are shown. The components are shown with a cluster extent of 30 voxels with a 1% false discovery rate with the threshold bar shown at the right of the panel. L: left; R: right.

**Table 3**  
Different non task-related networks with their respective areas of activation and their statistical level of task relatedness for the main cohort. NTRN: non-task-related network; BA: Brodmann areas.

NTRN	Activation region	BA	Task relatedness T-val (p-value)
Sup. parietal	Bilateral precuneus; bilateral sup/inf parietal gyrus; bilateral postcentral gyrus; bilateral middle occipital gyrus; bilateral middle cingulum.	7, 40, 5, 31	−0.36 (0.71)
Visual lat.	Bilateral sup/mid/inf occipital gyrus; bilateral fusiform gyrus; bilateral mid/inf temporal gyrus; bilateral lingual gyrus.	19, 18, 37, 7	1.03 (0.31)
Cerebellar	Cerebellum; vermis; pons.	–	0.87 (0.39)
Medial visual	Bilateral calcarine; bilareal lingual gyrus; bilateral cuneus; bilateral middle/superior occipital gyrus; bilateral precuneus.	19, 18, 7, 31, 1730	−1.12 (0.27)
Cingulate	Bilateral frontal medial gyrus pars orbitalis; bilateral frontal superior medial gyrus; bilateral anterior cingulate gyrus; bilateral rectus; bilateral caudate.	10, 11, 32	−0.73 (0.47)
Mesial temp	Bilateral temporal pole; bilateral parahippocampal gyrus; left middle temporal gyrus; bilateral hippocampus; bilateral fusiform gyrus; bilateral amygdala.	38, 34, 21, 28 35, 20, 28	−0.01 (0.99)
Right fronto parietal	Bilateral middle frontal gyrus; right superior frontal gyrus; right inferior frontal gyrus part orb/trian/oper; right frontal medial gyrus pars orbitalis; right frontal superior medial gyrus; right precentral gyrus; right anterior cingulate gyrus; bilateral middle cingulate gyrus; bilateral angular gyrus; bilateral superior/inferior parietal gyrus; bilateral precuneus; right supramarginal gyrus; right mid/sup occipital gyrus.	10, 9, 8, 6, 46 11, 47, 45, 4 32, 23, 40, 7 39	1.20 (0.23)

*Inferior Visual* (covering mainly the calcarine visual cortex), *Cerebellar*, *Mesial Temporal*, *right Fronto-Parietal*, *Posterior DMN* and *Superior Medial Fronto-Parietal* (see Table 4 for a description and statistical analysis).

#### Network engagements across blocks and word learning performance

*First Block:* the dAPMN, the dSMN, the dFPN and the vFPN were active during the first block, while the DMN was deactivated (Table 5 and Fig. 4). *Second block:* only the dAPMN remained significantly active, while the DMN was again significantly disengaged (Table 5 and Fig. 4). *Third block:* only the dAPMN was active during the third block (Table 5 and Fig. 4). *Fourth block:* the dAPMN and the dSMN were active during the last block (Table 5 and Fig. 4). The dAPMN engagement survived Bonferroni correction in all blocks and the dSMN in the first and fourth blocks.

Pearson skipped correlation analyses revealed that the strength of connectivity of the dAPMN during the second block was significantly correlated with word learning performance (no bivariate outliers detected:  $r = 0.40$ ,  $p < 0.047$ ; confidence intervals = 0.10, 0.65; see Fig. 5). A positive trend was also found during the first block although the  $p$  value did not reach the threshold for significance (no bivariate outliers detected:  $r = 0.34$ ,  $p = 0.08$ ; confidence intervals = 0.06, 0.60; Fig. 5).

## Discussion

In this study we identified several brain networks whose connectivity strength increases when adult participants are learning words from fluent speech. While being exposed to a novel language, three dorsal networks were engaged in two different and independent samples of subjects, and a fourth ventral network was significant for one sample

and marginal for the other. Following previous language processing models (Hickok and Poeppel, 2007; Rauschecker and Scott, 2009), the three networks were classified as dorsal language related networks. Specifically, an auditory-premotor network, a sensory-motor network (dSMN) and a fronto-parietal network (dFPN; see Fig. 2A, B and C) were identified. Thus, segregated sub-networks within the dorsal stream might have contributed differentially to the word learning process. Of these, the dAPMN was significantly active during all four blocks, while the dSMN was active during the first and last block (Fig. 4). The fourth task-related network was part of the ventral stream of speech processing (vFTN; see Fig. 2D). Expectedly, the default mode network showed an opposite pattern, as it was negatively correlated with the task. In addition, the block analysis engagement of the networks through the learning phase showed that although this network was significantly disengaged during the early presentation of the stimuli, it did not show a negative correlation during the last two blocks (Fig. 4). Interestingly, only the variability in the dAPMN directly correlated with the differences in individual learning performance during the second block of the task (and marginally during the first one; Fig. 5). These results suggest that connectivity between motor and auditory areas is important in the very early stages of learning when word forms are extracted from fluent speech. Importantly our results were obtained through Independent Component Analysis, a fully data-driven approach without any a priori assumption. Although these networks have been reported elsewhere during resting state (e.g. Beckmann et al., 2005; Smith et al., 2009), here we report their specific contribution to word learning.

The implication of the five reported networks in word learning was supported by the fact that our results were replicated in a second cohort of subjects. Consistent task-related networks were observed across both studies, in spite of different linguistic backgrounds (Spanish vs. German

**Table 4**  
Different non-task related networks with their respective areas of activation and their statistical level of task relatedness for the replication cohort. NTRN: non-task-related network; BA: Brodmann area.

NTRN	Activation region	BA	Task relatedness T-val (p-val)
Med. inf. visual	Bilateral calcarine; bilateral inf/mid occipital gyrus.	18,17	−0.38 (0.70)
Cerebellar	Cerebellum; vermis; pons	–	−1.93 (0.07)
Medial visual	Bilateral calcarine; bilareal lingual gyrus; bilateral cuneus; bilateral mid/sup occipital gyrus; bilateral precuneus	19,18,7,31,1730	−1.47 (0.16)
Posterior DMN	Bilateral frontal medial gyrus pars orbitalis; bilateral frontal superior medial gyrus; bilateral anterior cingulate gyrus; bilateral rectus; bilateral caudate; bilateral precuneus; bilateral posterior cingulate gyrus.	10,11,32,31	0.10 (0.92)
Mesial temporal	Bilateral temporal pole; bilateral parahippocampal gyrus; bilateral mid/inf temporal gyrus; bilateral hippocampus; bilateral fusiform gyrus; bilateral amygdala.	38,34,21,28 35,20,28	1.78 (0.095)
Right fronto parietal	Right mid/sup frontal gyrus; right inferior frontal gyrus part orb/trian/oper; right frontal superior medial gyrus; bilateral angular gyrus; right supramarginal gyrus; bilateral sup/inf parietal gyrus; right postcentral gyrus.	10,8,9,6,46,45,47,11,40,7,39	−1.46 (0.16)
Superior medial fronto-parietal	Bilateral frontal superior medial gyrus; bilateral superior middle/frontal gyrus; bilateral anterior cingulate gyrus; bilateral angular; left supramarginal gyrus; bilateral inferior parietal gyrus	10,8,9,6,40,39	−1.05 (0.30)

**Table 5**

Statistical indexes of task relatedness for each of the four blocks that composed the word learning task. TRN: task-related network; dAPMN: dorsal auditory-premotor network; dSMN: dorsal sensory-motor network; dFPN: dorsal fronto-parietal network; vFTN: ventral fronto-temporal network; DMN: default mode network.

Block	TRN	T-value	d.f.	T-value
1	dAPMN	17.6	26	0.001 <sup>a</sup>
	dSMN	4.74	26	0.001 <sup>a</sup>
	dFPN	2.67	26	0.015
	vFPN	2.13	26	0.043
	DMN	-2.85	26	0.009
2	dAPMN	13.43	26	0.001 <sup>a</sup>
	dSMN	0.29	26	0.77
	dFPN	1.57	26	0.12
	vFPN	0.36	26	0.72
	DMN	-2.79	26	0.01
3	dAPMN	18.26	26	0.001 <sup>a</sup>
	dSMN	0.93	26	0.36
	dFPN	1.12	26	0.27
	vFPN	-0.53	26	0.60
	DMN	-1.69	26	0.10
4	dAPMN	15.55	26	0.001 <sup>a</sup>
	dSMN	4.4	26	0.001 <sup>a</sup>
	dFPN	0.84	26	0.40
	vFPN	-0.03	26	0.97
	DMN	-1.44	26	0.16

<sup>a</sup> Survived the correction for multiple comparisons.

learners with Spanish and German phonemes respectively), variable MRI technology (two different 3 T scanners) and acquisition parameters (see Material and Methods section). This further backs our claim, as false positives are not likely to replicate across independent samples (Bennet et al., 2009; Button et al., 2013; Lieberman and Cunningham, 2009).

#### Dorsal networks for word learning

We found three networks that belong to the dorsal fronto-temporo-parietal stream of language processing (Hickok and Poeppel, 2000; Saur et al., 2008). First, the dorsal *Auditory-Premotor Network* (Fig. 2A), connecting the pSTG (including the Spt region, located within the Sylvian fissure at the parieto-temporal boundary), the PMC and the bilateral SMA, has been associated with auditory-motor integration (Hickok and Poeppel, 2000; Liberman and Whalen, 2000), an inherent mechanism of language processing. Interestingly, in our study this was the only network that (i) was significantly engaged during the four blocks; (ii) that showed the most robust engagement, as it did survive multiple comparisons corrections in the different analyses; and (iii) whose connectivity strength was directly correlated with word learning performance, marginally during the first and significantly during the second block of the learning phase. These two properties fit well with a recent study in which we reported the importance of the direct left segment of the arcuate fasciculus for word learning and the functional connectivity between the areas connected by this fascicle (López-Barroso et al., 2013). In this previous study nevertheless, the analyses were restricted to the areas of theoretical interest and therefore whole brain connectivity was not assessed. The consistent finding in this different study with an additional replication in a cohort from a different language background and with a data-driven approach gives further strength to the results.

The importance of motor regions for language processes is also supported by the implication of the PMC in speech perception (Meister et al., 2007; Pulvermüller et al., 2006; Wilson and Iacoboni, 2006). Also, Rauschecker and Scott (2009) proposed a unified function of the dorsal stream in which the PMC informs the auditory system about the planned motor sequences that are about to happen (overtly or covertly), and this is matched with feedback signals from auditory areas (pSTG), closing the loop. The template-matching function of this network can therefore have a particularly important role during word

learning from speech (Rodríguez-Fornells et al., 2009). Our results suggest that this function is particularly important during the initial contact with the new language, when word forms need first to be extracted, to be then kept in working memory and finally memorized.

Second, sensory and motor regions were also engaged during the task, as supported by the identification of the dorsal *Sensory-Motor Network* (dSMN, Fig. 2B). Primary related to motor functions (Biswal et al., 1995), this bilateral network comprises regions from the precentral and postcentral gyri in addition to supplementary and pre-supplementary motor and cingulate areas. These regions have been related to speech production (Alario et al., 2006; Chauvel et al., 1996; Crosson et al., 2001; Krainik et al., 2004; Ziegler et al., 1997). Although its exact role is still unclear, the anterior part of the SMA is reliably involved in sequence learning (Hikosaka et al., 1996; Penhune and Steele, 2012). This network was significantly engaged during the first and the last blocks of learning, suggesting that the planning of the articulatory movements (Lau et al., 2004) required for the covert rehearsal (López-Barroso et al., 2011) occurs to a greater extent during the early contact with the new language for the sequences of syllables (first block) and then in the last block when word chunks are already segmented and rehearsed for memorisation.

Third, a left dorsal *Fronto-Parietal Network* (dFPN, Fig. 2C) comprising the inferior and superior parietal cortex, the IFG, the dorsolateral prefrontal gyrus and the PMC was identified. This network can be considered a classical language network. Indeed, the inferior parietal lobe has been previously identified as an important region in vocabulary learning and second-language learning (Golestani and Pallier, 2007; Leh et al., 2007; Mechelli et al., 2004). This whole network overlaps with the attentional network (Corbetta and Shulman, 2002; Salmi et al., 2009) and includes the supramarginal gyrus (SMG), involved also in the maintenance of phonological information in working memory through an attentional controller mechanism or through short-term storage (Awh et al., 1996; Chein et al., 2003; Cowan, 2008; Ravizza et al., 2004). The appearance of this network suggests an engagement of both working memory and attention functions in learning of phonological word forms (Baddeley, 2003; De Diego-Balaguer and Lopez-Barroso, 2010; López-Barroso et al., 2011; Rodríguez-Fornells et al., 2009).

#### Ventral network for word learning

The ICA analysis also revealed a ventral *Fronto-Temporal network* (Fig. 2D), which comprises the bilateral anterior temporal areas, the IFG area (including the frontal operculum [FOP]) as well as the bilateral striatum. Although classically associated to conceptual-semantic analysis (Binder et al., 2009; Hickok and Poeppel, 2007; Lambon Ralph et al., 2012; Patterson et al., 2007), the implication of the ventral network in auditory object recognition has been also proposed, allowing categorization of the incoming auditory stimulation as new or familiar (Leaver and Rauschecker, 2010; Rauschecker and Scott, 2009; Zatorre et al., 2004). In agreement with this, and regarding the task used in the current study, the ventral stream could have a role in the recognition of the phonological chunks (new words) once they have been segmented. Its engagement during word form learning, even when there is no semantic component, agrees with previous results indicating a prominent role of this ventral stream when support to the dorsal stream is needed (López-Barroso et al., 2011; Saur et al., 2010). In addition, the caudate nucleus forms part of this network, which agrees with the importance of this area for the concatenation of sequences forming a chunk (Koechlin and Jubault, 2006) in artificial language learning from visual or auditory sequences (Bahlmann et al., 2008; De Diego-Balaguer et al., 2008; Doeller et al., 2006; Lieberman, 2000). Nevertheless, the limited replication of this network, marginally significant in the main cohort, may go in the direction of a secondary implication of this network compared to the dorsal networks previously described.



Interestingly, the four networks identified in the study seem to be organized in a caudal-dorsal to rostral-ventral fashion (see Fig. 6). This organization fits well with studies proposing a hierarchical functional organization of the lateral frontal cortex in relation to cognitive control. Applied to sequential linguistic processing (e.g. phonemes, syllables,

words in sentences) this could mean that rostral (anterior) regions control more abstract and complex structures and caudal (posterior) regions process and control more concrete information (Badre and D'Esposito, 2009; Bahlmann et al., 2012, 2014; Christoff et al., 2009; Koehlin and Jubault, 2006).

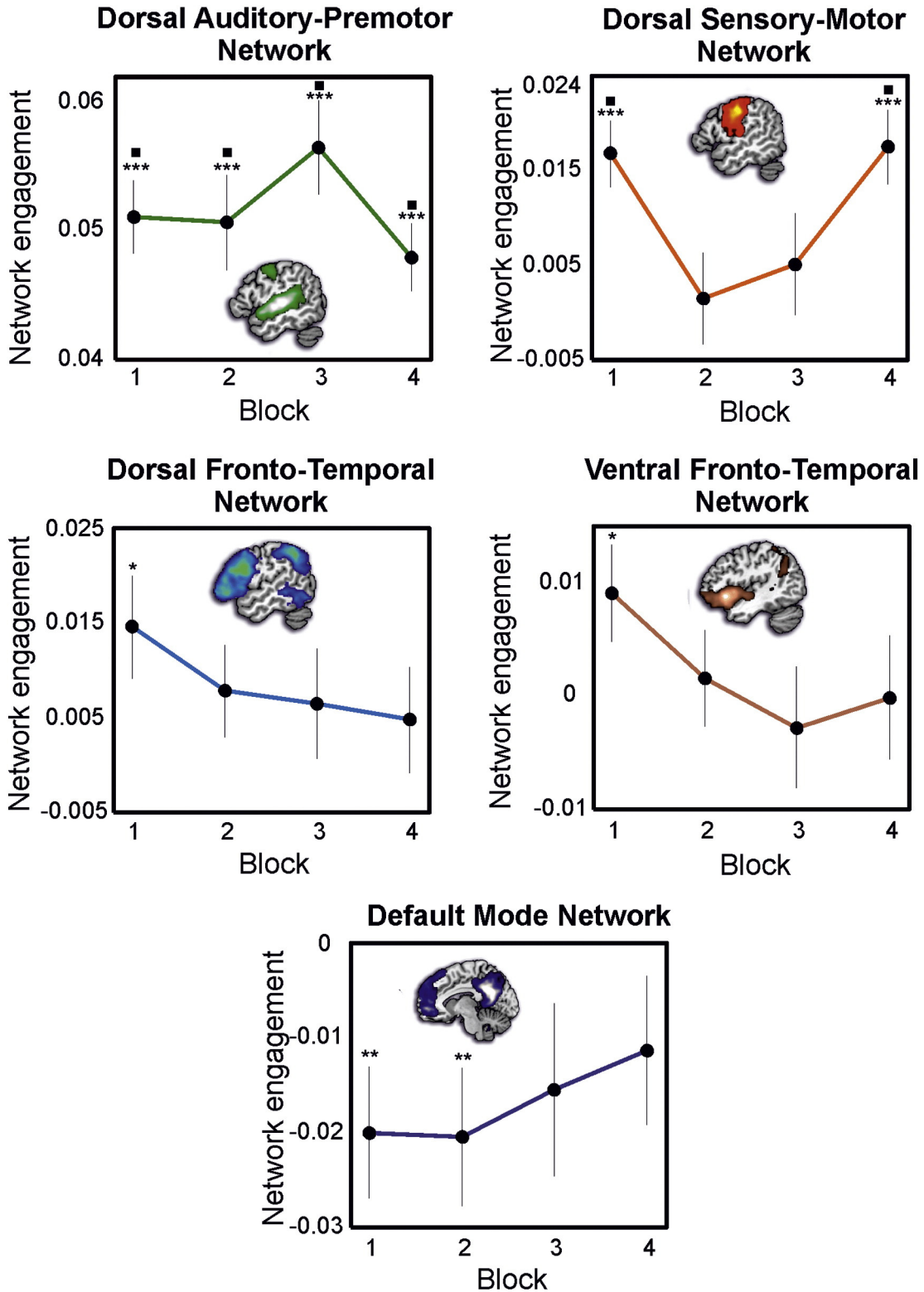
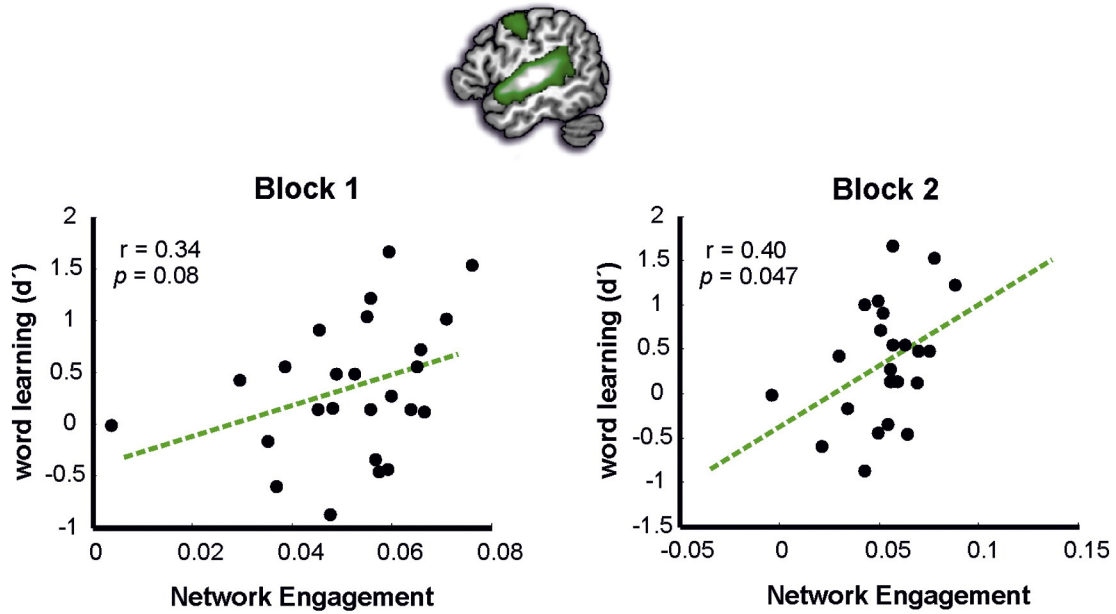


Fig. 4. Illustration of the average network engagement for each block and network for the main cohort. Bars indicates SEM. \* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$ ; • survived the correction for multiple comparisons.

### Dorsal Auditory-Premotor Network



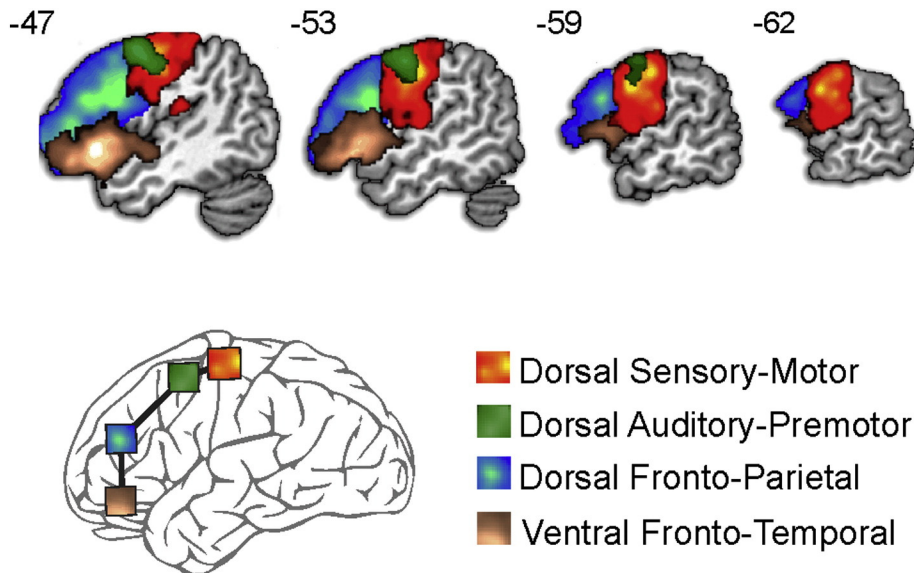
**Fig. 5.** Scatter plots showing the relationship between network engagement and word learning performance in block 1 and block 2 for the dorsal auditory-premotor network. Correlation indexes and the associated *p* values are depicted on each plot.

#### The default mode network

The *Default Mode Network (DMN)*; see Fig. 3) was negatively correlated with the task. This finding is consistent with the characteristics of the DMN. Since it was first described (Raichle et al., 2001), the DMN has been related to the gathering of incoming sensory information at rest and has been reported as deactivated during active tasks (Kuperberg et al., 2003; Mestres-Missé et al., 2008; Smith et al., 2009). The block-wise analysis showed that the DMN was disengaged during the first two blocks of stimulation. The concomitant correlation in

these blocks with learning performance for the dAPMN may indicate that as learning increases, the DMN gradually engages since the task progressively becomes less demanding.

Finally, the present study has some limitations that should be faced in future investigation. On the one hand, the correlation with behavior allowed us to see the networks whose engagement had an effect on the accuracy differences found among participants. However, other networks showed variations in their engagement with the task and although the non-significant correlation with performance indicates that they might not determine differences in accuracy, it does not



**Fig. 6.** Illustration of the frontal region covered by each of the four networks retrieved in the left hemisphere for the main cohort. For display purposes, only the frontal clusters of each network are shown in this figure. MNI coordinates in millimeters are shown in the top left corners of each slice.

mean that they are not involved in learning. Therefore, with this approach, we can spot and segregate the different networks involved in the task but we are unable to know their specific contribution to language learning. On the other hand, for this reason also, although we had a strong hypothesis linking the *Auditory-Premotor Network* to word learning performance, the fact that other networks were also engaged during learning increased the number of correlations to be performed. Thus, although the correlations were performed with a specific robustness test and were limited to those networks surviving multiple corrections and replication, the behavioral correlations reported would have been sounder with a multiple comparison correction. Finally, it is worth mentioning that in spite of the advantages of using ICA to unveil unconstrained brain connectivity compared to classical GLM fMRI analysis, the interactions between networks are not revealed with ICA analysis. Further studies are needed in order to assess the direct influence and direction of the coupling that each network (or nodes within these networks) exerts over the others (i.e., effective connectivity) during language learning.

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