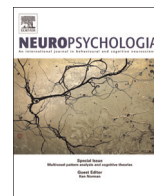




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Complex brain network properties in late L2 learners and native speakers

Alejandro Pérez^{a,*}, Margaret Gillon Dowens^b, Nicola Molinaro^{a,c}, Yasser Iturria-Medina^d,
Paulo Barraza^e, Lorna García-Pentón^a, Manuel Carreiras^{a,c,f}

^a Basque Center on Cognition Brain and Language, BCBL, Donostia-San Sebastián, Spain

^b University of Nottingham Ningbo Interdisciplinary Centre on Research in Neuroscience, UNNICORN, Ningbo, China

^c Ikerbasque, Basque Foundation for Science, Bilbao, Spain

^d Montreal Neurological Institute, McGill University, Montreal, Quebec, Canada

^e Centro de Investigación Avanzada en Educación, CIAE, Universidad de Chile, Santiago 8330014, Chile

^f Departamento de Lengua Vasca y Comunicación, EHU/UPV, Bilbao, Spain

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ABSTRACT

Whether the neural mechanisms that underlie the processing of a second language in highly proficient late bilinguals (L2 late learners) are similar or not to those that underlie the processing of the first language (L1) is still an issue under debate. In this study, a group of late learners of Spanish whose native language is English and a group of Spanish monolinguals were compared while they read sentences, some of which contained syntactic violations. A brain complex network analysis approach was used to assess the time-varying topological properties of the functional networks extracted from the electroencephalography (EEG) recording. Late L2 learners showed a lower degree of parallel information transfer and a slower propagation between regions of the brain functional networks while processing sentences containing a gender mismatch condition as compared with a standard sentence configuration. In contrast, no such differences between these conditions were detected in the Spanish monolinguals. This indicates that when a morphosyntactic language incongruence that does not exist in the native language is presented in the second language, the neural activation pattern is configured differently in highly proficient late bilinguals than in monolinguals.

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1. Introduction

Previous research on late L2 acquisition measuring the electrophysiological correlates of language processing using the event related potential (ERP) technique do not display a consistent picture regarding whether similar or different neural patterns underlie sentence processing in monolinguals and highly proficient L2 learners (Bowden et al., 2013; Chen et al., 2007; Friederici et al., 2002; Gillon Dowens et al., 2011; Gillon Dowens et al., 2010; Hahne and Friederici, 2001; Hahne et al., 2006; Isel, 2007; McLaughlin et al., 2010; Morgan-Short et al., 2012a, 2010, 2012b; Mueller et al., 2005; Ojima et al., 2005; Osterhout et al., 2008; Pakulak and Neville, 2011; Rossi et al., 2006; Steinhauer et al., 2009; Tokowicz and MacWhinney, 2005; Weber-Fox and Neville, 1996). However, ERPs (and also spectral power estimations) only reflect local activation of large groups of neurons, while it is

thought that the physiological bases of information processing and mental representation are provided by functional networks (Bressler, 1995). In this sense, the ERP approach can be considered a somewhat limited perspective in investigating the biological bases of language acquisition, as it provides only measurements of local activation but not critical information about the relations established between different areas and the networks that emerge from these. Thus, detection of a similar ERP pattern across two groups of participants or two conditions does not necessarily mean similar neural substrates or that equivalent cognitive processing is taking place.

An alternative to ERPs, in addressing whether the neural mechanisms that subserve the processing of the first language (L1) are the same or different from those underlying the L2, is to use brain complex network analysis. This approach, based on a mathematical framework called graph theory, considers the brain as a complex system or network: the brain is modeled as a graph whose nodes (or vertices) represent defined regions, with the links (or edges) between them representing functional (or structural)

* Corresponding author. Fax: +34 943 309 052.

E-mail address: a.perez@bcbl.eu (A. Pérez).

connections (Bassett and Gazzaniga, 2011; Bullmore and Sporns, 2009, 2012; Sporns, 2013; Stam and Reijneveld, 2007). The capacity of theoretical complex analysis to explain the brain's basic organization relies strongly on how much the estimated network represents the underlying neurobiological system. In this sense, it seems more justified to use this type of analysis for anatomical (structural) networks, which are thought to be more invariant over short time scales. However, as the core question of the emergence of coherent behavior and cognition is presumed to be implemented by the dynamic links established between different areas, graph analysis has been here extrapolated to brain functional connectivity, an application now possible due to the rapid methodological development of new analytical tools (for electrophysiology see for example Greenblatt et al. (2012); Sakkalis (2011)). In functional connectivity, generally, the 'links' are statistical measures of temporal dependence between indirect measures of neuronal activities, an approach which constitutes a different conceptualisation of connection (Friston, 2011). Caution in the implementation and interpretation of graph analysis is therefore necessary at the functional level (Sporns, 2014).

At the brain functional connectivity level it could be said that there are two kinds of modalities: (i) voxel-based modalities such as functional magnetic resonance imaging (fMRI) or positron emission tomography (PET) with nodes in the measurement space and (ii) sensor-based modalities such as EEG, magnetoencephalography (MEG) and near-infrared spectroscopy (NIRS) in which the nodes are the sensors (De Vico Fallani et al., 2014). The former are highly informative but still have important constraints, with non-trivial factors such as brain parcellation definition (atlas) or number of nodes impacting on the results and influencing the ability to compare across studies or techniques. On the other hand, sensor-based modalities have the problem of volume conduction and we therefore have a choice between ignoring this effect (resulting in a biased non-neural dependence) or addressing it. Two possible ways to address the issue are to use cortical source reconstructions or to choose a functional connectivity measure that attenuates volume conduction effects (De Vico Fallani et al., 2014).

There is a wide range of complex network measurements (topological parameters) reflecting different properties of the networks (Rubinov and Sporns, 2010). For example, measures of integration characterize the ability to rapidly combine specialized information from distributed regions by estimating the ease with which the regions communicate. They are commonly based on the concept of path, which is a sequence of distinct nodes and links, representing sequences of statistical associations in the case of functional networks (Rubinov and Sporns, 2010). Two common measures of integration are path length (L) and global efficiency (E_{glob}). L is the average shortest distance (path) between all pairs of nodes in the network (Watts and Strogatz, 1998) while E_{glob} is the average inverse shortest path length (Latora and Marchiori, 2001). On other hand, there are also measures of node centrality, which assess the importance of individual nodes. Higher centrality is associated to those nodes that act as bridges between the other nodes (Bassett et al., 2006; Dall'Asta et al., 2006; Freeman, 1977; Honey et al., 2007). The importance (centrality) is sometimes based on the idea that those nodes that participate in many short paths within a network have an important control of information flow (Freeman, 1978). For instance, the betweenness centrality measure consists in the fraction of all shortest paths in the network that contain a given node (Rubinov and Sporns, 2010). Nodes with high values of betweenness centrality participate in a large number of shortest paths.

Although there are different valid methodological decisions about what is considered to be a node and what is considered to be a link, essentially, the definition of these topological measures is invariable and independent of the network modeled. However,

it is essential to interpret the results according to the nature of the signals analyzed. As electrophysiological signals indirectly reflect the activity fluctuations of underlying neuronal groups, once the conduction volume effects are controlled in an electrophysiological network reconstruction, it is then feasible to assume the electrodes to be unique/independent nodes that interrelate mutually and define a consistent network. In sum, all network topological measures retain their classical interpretations (Bullmore and Sporns, 2009; Iturria-Medina, 2013; Rubinov and Sporns, 2010), with the particularity that these would now represent potential neuronal interactions.

In the context of cognitive neuroscience, these measures have a tentative physiological interpretation. The average and distribution of the L determines the "compactness" of the neural network, with shorter path lengths meaning that information can be propagated faster between regions of the brain. The E_{glob} reflects the degree of parallel information transfer; here a high global efficiency value may indicate higher parallel information transfer in the brain system (Iturria-Medina, 2013). In the case of the betweenness centrality measure, nodes with higher values are presumed to have a higher relative importance in the functioning of the whole brain network defined. In general, it could be said that these measures capture the global management of information flow and the relative performance of particular areas. Complex network analysis thus enriches comprehension of brain mechanisms in general (Rubinov and Sporns, 2010), shifting the research perspective from 'foci' to 'network' (van Diessen et al., 2013). This analysis can therefore be valuable in ascertaining whether a particular neural pattern of activation in L2 behaves in a native-like way or not. In fact, in studies where other approaches do not show differences between the neurophysiological patterns subserving cognitive performance in L1 and L2 and the hypothesis of similar neural substrates for both languages is therefore posited, complex network analysis can provide key information to support or to question this assumption.

In this study, we specifically assess for the time-varying topological properties of functional networks as extracted from the EEG data (Chavez et al., 2010; Valencia et al., 2008). This method involves studying the time-frequency dependencies of the functional brain networks, thus offering topological parameters which describe the brain network configuration at different time points. Similar to Chavez et al. (2010), the nodes are represented by the recording sites (electrodes) and the links between them by the Phase-Locking Value (PLV). The PLV method (and synchrony methods in general) measure the relative stability of the difference of phases between two signals, here EEG signals, and then capture when neuronal groups that oscillate in specific frequencies enter into precise phase-locking over a limited period of time (Le Van Quyen et al., 2001). Neural synchrony is involved in the large-scale transient integration of numerous functional areas widely distributed over the brain which is required for normal cognitive operations (Varela et al., 2001). In other words, PLV (and long-range synchrony methods in general) allow extraction of the functional network connectivity patterns from EEG, as it is assumed that coherent electrophysiological activity can span the multiple, spatially distinct brain regions that make up a functional network (Fries, 2005; Singer, 1999).

In a previous EEG study of late (adult) L2 acquisition, highly proficient L2 learners of Spanish (native English speakers) showed both different and similar ERP patterns to monolingual native Spanish speakers when they performed morphosyntactic agreement tasks (Gillon Dowens et al., 2010). Interestingly, there was a similar pattern between native speakers and the L2 group when processing gender disagreement between article and noun at the beginning of sentences visually presented word-by-word. Morphosyntactic gender agreement, however, is an L2 (Spanish) trait

not present in the L1 (English) of these participants, so no transfer of this feature to the L2 is possible, suggesting the plausibility of differential underlying neural processes in both groups which were not captured by the ERP technique.

In the present study, by using data from Gillon Dowens et al.'s (2010) study, we will concentrate on this local gender disagreement between article and noun. As the performance of L2 late learners in the gender agreement task showed more variability than that of native speakers, we selected a subset of participants from the two groups that were matched in performance (error rates) in the task. This means that the equivalence in the proficiency of both groups will be guaranteed not only by taking into account similarity in the off-line tests but also equivalent behavioral performance in the on-line task. This is important, since the question of L2 proficiency is a key factor to be taken into account when questions of native-like processing are addressed (Kotz, 2009; Mueller et al., 2005) and if this is not controlled for, results can be quite different (Hahne, 2001; Weber-Fox and Neville, 1996).

Summarizing, here we provide a different perspective to studies of late L2 acquisition which emphasize focal brain activity (for example ERPs), by employing a complex network analysis approach. Specifically, we assess for similarities and differences in the time-varying topological properties of the functional networks, as extracted from EEG data (Chavez et al., 2010; De Vico Fallani et al., 2008; Dimitriadis et al., 2010; Valencia et al., 2008), associated to the processing of gender mismatch between article and noun at the beginning of Spanish sentences in two groups of participants: a Spanish monolingual group and a group of late learners of Spanish whose native language is English. We expect that this complex network approach will provide new information about language organization and morphosyntactic processing in late L2 acquisition, as manifested by EEG functional networks, in terms of functional cooperation and interaction. Specifically, we predict that possible differences in the topological parameters will be reflected in theta band (4–7 Hz) because this specific range of frequencies is consistently modulated in relation to processing of correct and syntactically anomalous sentences (Bastiaansen et al., 2002; Hald et al., 2006; Pérez et al., 2012). We also predict that for the late learners when the processing of a mismatching word takes place, in an effort to solve the inconsistency, less parallel information transfer in the brain system will occur (i.e. smaller E_{glob} for the mismatch condition) and the neural networks associated will have longer paths (i.e. smaller L for the Agreement condition) as compared to when a typical sentence is processed.

2. Methods

2.1. Participants

Event-related potential data of the present participants, plus data from another 22 participants (11 more in each group) were previously published (Gillon Dowens et al., 2010). Our subsample was selected to achieve a similar percentage of correct responses between groups also in the online tasks, to guarantee as far as possible real equivalence in the proficiency of both groups.

2.1.1. Late bilingual group

This was composed of 12 native speakers of English who were late learners of Spanish (mean age = 47.4 years, $std = 7.8$, range 35–60, 10 female). The participants were interviewed by a trained native speaker of English and a trained native speaker of Spanish to evaluate their comprehension and fluency in both languages. All were judged highly proficient in speaking, reading and understanding Spanish. They filled in a self-rating questionnaire about their language background: the age of acquisition (AoA) of Spanish

and English, the time spent in each language environment, their daily use of Spanish and English (in percentage) and their proficiency in both languages (on a scale from 1-very poor level to 5-perfectly fluent) for speaking, listening, reading and writing. All of them started to learn Spanish after the age of 20 and had at least 12 years of immersion in a Spanish environment (range: 12–33, mean: 22.1). The results indicated that the participants used Spanish on a daily basis and rated their competence in Spanish as being good to perfect (the average for speaking was 4, listening 4, reading 5, and writing 3). After the experiment, they also filled in a grammar test of 90 questions on noun–adjective agreement that included the experimental items. The results from this confirmed that off-line, the participants were able to choose the correct form of the adjective in terms of gender and number agreement, at 98% ($SD = 0.82$) accuracy.

2.1.2. Spanish native-speaker group

This was composed of 12 native speakers of Spanish (mean age = 45.8 years, $std = 7.5$, range 35–60, 2 females). After the experiment, they also filled in the short grammar test. The results confirmed that off-line, the participants were able to choose the correct form of the adjective at 99% ($SD = 0.58$) accuracy.

The participants in both groups were matched in terms of educational background and socioeconomic status. All participants were right-handed, as assessed by the Edinburgh Handedness Inventory (Oldfield, 1971), with normal or corrected-to-normal vision and no history of neurological or psychiatric impairment according to self-report.

2.2. Materials

The experimental materials related to the data used here consisted in a list of 80 sentences: 40 correct sentences and 40 sentences showing article–noun gender disagreement at the beginning. See examples below

- (1) Agreement: *El suelo está plano y bien acabado.*
(*The_{masc.-sing.} floor_{masc.-sing.} is flat and well finished.*)
- (2) Gender Disagreement: *La suelo está plano y bien acabado.*
(*The_{fem.-sing.} floor_{masc.-sing.} is flat and well finished.*)

Basically, conditions consisted in the same sentences but combining different gender forms (agreeing or disagreeing), making the conditions equivalent in terms of mean length and frequency of the words. Each participant saw each sentence (from the original list of 120) in only one form but each sentence form occurred several times across subjects. All the target items were medium to high frequency words (mean = 1.15, $SD = 0.5$), contained between four and nine letters (mean = 5.65, $SD = 1.03$) and between two and four syllables (mean = 2.3, $SD = 0.48$) (Duchon et al., 2013).

Experimental material also shown to participants but the associated data of which was not used here included 120 sentences that manipulated the agreement relationship in the middle of the sentence, 40 sentences that manipulated number agreement at the beginning of the sentence and 80 well-formed sentences that included nouns with opaque or irregular gender and adjectives with neuter gender to avoid strategies based on purely orthographic features (for a description of the full set of materials see Barber and Carreiras (2005); Gillon Dowens et al. (2010)).

2.3. Procedure

Participants were seated comfortably in a darkened sound-attenuated chamber with a high-resolution monitor positioned at eye level 80–90 cm in front of them. The sentences were visually presented word by word using Presentation software. The EEG was

simultaneously recorded with a 64-channel BrainAmp system (Brain Products GmbH). All the words were displayed in light-gray lowercase Arial 36 against a black background. Participants performed a grammatical decision task. They were instructed to press one of two keys (L and S) on a keyboard to indicate whether the sentence was grammatically correct or not. For half of the participants, the right key (L) was used to signal the “yes” response and the left key (S) was assigned to the “no” response. For the remaining participants, the order was reversed.

The sequence of events in each trial is described as follows: First, a fixation point (*) appeared in the center of the screen and remained there for 700 ms. This fixation point was followed by a blank screen interval of 300 ms, and then the sentence was displayed word by word. Each word appeared for 300 ms and was followed by a 300-ms blank interval. At the end of the sentence, a question mark cue to respond was presented and remained there up to a maximum of 2000 ms or until the participant’s response. The inter-trial interval varied randomly between 1000 and 1500 ms. Participants were asked to avoid eye movements and blinks if possible during the interval starting from the fixation point until response was given and were instructed to favor accuracy over speed in their responses. A practice session of five trials was given. The sentences were presented in three blocks of approximately 14 min each, with two short rest breaks. The whole experiment lasted approximately 90 min, including set-up time.

2.4. EEG pre-processing

Fig. 1 Schematically illustrates the basic steps of the time-varying brain complex network approach, similar to that proposed by Chavez et al. (2010).

Electrophysiological data was acquired using 58 Ag/AgCl electrodes (Fig. 1, panel a) that were mounted in an elastic cap (10–10 system; ElectroCap International, Eaton, OH). Linked earlobes were used as reference. Eye movements and blinks were monitored with six additional electrodes providing bipolar recordings of the horizontal and vertical electrooculogram (EOG). Interelectrode impedances were kept below 10 k Ω . Data were acquired at a sampling rate of 250 Hz. All the analyses were performed using MATLAB (The MathWorks Inc.). EEG signal was processed using EEGLAB toolbox (Delorme and Makeig, 2004). Signal was off-line

re-referenced to the average activity of the two mastoids. A high-pass filter of 1 Hz was applied before performing an independent component analysis (ICA) algorithm type Biased Infomax (Makeig et al., 1997). Components were visually inspected searching for those accounting for ocular movements in order to remove them from data. EOG sensors and frontal electrodes Fp1, Fp2 and Fpz were then discarded as they were recording mainly ocular movement activity. The EEG data was then segmented into 3000 ms epochs, including a 800 ms baseline (Fig. 1, panel b). Note that all steps until here are common data-processing steps to obtain ERPs.

2.5. Complex network analysis

The next step is estimation of the functional brain networks. Functional links between all pairs of sensors were defined via the PLV (Lachaux et al., 1999) using a custom-written program. To compute the PLV values, we used a complex Morlet wavelet function $\omega(t, f_0) = A \exp(-t^2/2\sigma_t^2) \times \exp(i2\pi f_0 t)$. Normalization factor A was set to $A = (\sigma_t \sqrt{\pi})^{-1/2}$. $\sigma_t = m/2\pi f_0$, m is a constant that defines the compromise between time and frequency resolution, and f_0 is the center frequency of the wavelet. Hence, in the time domain, its real and imaginary parts are a cosine and a sine, respectively, of which the amplitude envelope is a Gaussian with a standard deviation of σ_t . In the frequency domain, the Morlet wavelet is also a Gaussian with a standard deviation σ_f given $m = f_0/\sigma_f$. Here, m was chosen to be 7. By means of this complex wavelet transform, an instantaneous phase $\phi_i^{\text{trial}}(t, f)$ is obtained for each frequency component of signals $i = 1, \dots, M$ at each repetition of the stimulus (trial). The PLV between any pair of signals (i, k) is inversely related to the variability of phase differences across trials

$$PLV_{i,k}(t, f) = \frac{1}{N_{\text{trials}}} \left| \sum_{\text{trial}=1}^{N_{\text{trials}}} \exp(j(\phi_i^{\text{trial}}(t, f) - \phi_k^{\text{trial}}(t, f))) \right|,$$

where N_{trials} is the total number of trials. If the phase difference varies little across trials, its distribution is concentrated around a preferred value and PLV ~ 1 . In contrast, under the null hypothesis of a uniformity of phase distribution, PLV values are close to zero

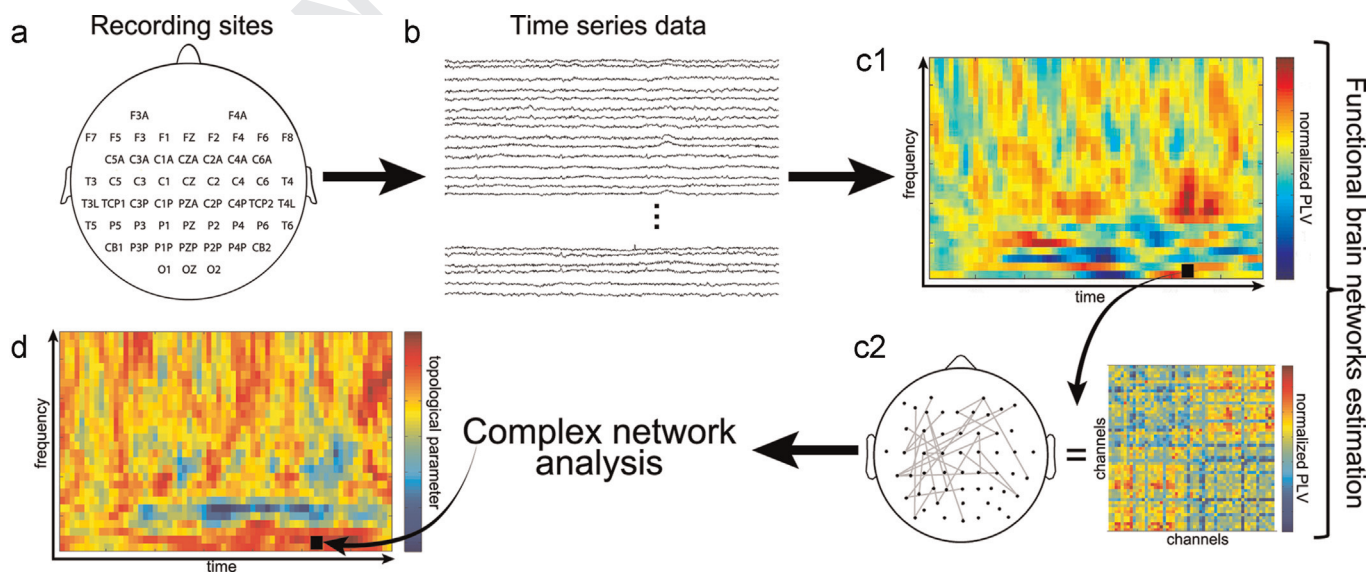


Fig. 1. General schema for the extraction of the time-varying brain networks: (a) flat representation of the 55 electrode positions from which EEG activity was recorded; (b) time series signals that after epoching are used to estimate the PLV in each condition; (c1) time–frequency estimation of the PLV; (c2) connectivity matrices are extracted at each point of the time–frequency space which can be represented as an undirected weighted adjacency matrix (c2 right) or as scalp topography with lines denoting connections (c2 left). Complex network analyses are then performed allowing (d) a time–frequency representation for each topological parameter estimated.

(Chavez et al., 2010).

Briefly: in each trial, for any electrode pair PLV was computed. PLV assesses for the phase difference between two signals and its computation was based on the phase information obtained from the wavelet transform. This was done specifically in 40 ms steps and a frequency range from 3 to 30 Hz. PLV results are collapsed across trials of each condition (a parallel to the grand average in ERPs). PLV range is from 0 to 1, indicating random or perfect synchronization respectively. As the PLV is an index of long-distance neural synchrony, the final result is a time–frequency representation of the functional networks (Fig. 1, panel c1). Note that the commonly-presented time–frequency plots of the PLV values as in Fig. 1, panel c1, consist in an averaging of all electrode-pair data. This means that to each time–frequency point (represented by a black square dot in the figure) there corresponds a functional network.

PLV measures were normalized relative to a baseline, in a procedure commonly used in the event-related spectral perturbation (ERSP) (Makeig et al., 2004). Here, this was done specifically by using the 200 ms baseline before the onset of the target word. The normalized signal (S_N) was obtained by subtracting the average activity of the baseline (μ) from the raw signal (S) and then dividing by the standard deviation of the baseline (σ), in a frequency-by-frequency manner: $S_N = (S - \mu) / \sigma$.

Every time–frequency-specific functional brain network derived from PLV data serves as a matrix of coupling coefficients that link electrode nodes. This connectivity matrix (adjacency matrix) is represented on the right of Fig. 1, panel c2 but can also be depicted, in the EEG field, by a scalp topography graph showing the electrodes and lines between them representing the links (see Fig. 1, panel c2, the left figure), these being equivalent representations of the same data.

Then, before proceeding with the calculation of the graph measures, the associated connectivity backbones were estimated (Hagmann et al., 2008) over the matrix (55×55) composed of undirected and weighted edges consistent in the normalized PLV values. This step is included because graph measures on these networks are influenced by average connection strength, the range of connectivity values and by the noisy and spurious connections contained in these weighted networks (Tewarie et al., 2014). In other words, it is performed in order to reduce the number of spurious connections present in each normalized PLV network (Stam et al., 2014). This procedure removed from the individual (time–frequency-specific) functional graphs those electrode–electrode links with a low degree of evidence supporting the existence of a functional interrelation between the underlying neuronal groups. Ideally, this retains in each final functional graph only the pair-wise links associated to direct functional interrelations. Briefly, the backbone estimation procedure works as follows (Hagmann et al., 2008): a) the maximum spanning tree of the PLV graph is extracted, i.e. the acyclic subset of links that connects all the nodes in the studied graph and for which the total PLV weight is maximized, and then b) for each node, additional links are added in order of their weight until the node is “linked” to at least other 4 nodes.

Next, complex network analyses were performed on each individual (time–frequency-specific) backbone PLV matrix.

The topological parameter L for a given network G was defined as the mean of geodesic lengths d_{ij} over all pairs of nodes i and j , according to the following formula:

$$L = \frac{1}{n(n-1)} \sum_{\substack{i,j \in G \\ i \neq j}} d_{ij}$$

In this study, we assumed that the physical length of an arc

connecting nodes i and j is inversely proportional to the strength of the analyzed connection (Iturria-Medina et al., 2008), i.e. $l_{ij} = 1/w_{ij}$. Thus, the shortest path length d_{ij} is finally computed as the smallest sum of the arc lengths throughout all the possible paths from node i to node j . Note that for the particular case of unweighted graphs, $l_{ij} = 1$ for all arcs and the geodesic length d_{ij} reduces to the minimum number of arcs traversed to get from i to j .

The E_{glob} parameter is then defined as (Watts and Strogatz, 1998)

$$E_{glob} = \frac{1}{n(n-1)} \sum_{\substack{i,j \in G \\ i \neq j}} \frac{1}{d_{ij}}$$

The betweenness centrality is mathematically defined as follows: for weighted networks, if σ_{kj}^w is the number of paths from node k to node j , and $\sigma_{kj}^w(i)$ is the number of these paths passing through node i , the weighted betweenness centrality of i is (Dall’Asta et al., 2006)

$$b_i^w = \sum_{\substack{k,j \in G \\ k \neq j \neq i}} \frac{\sigma_{kj}^w(i)}{\sigma_{kj}^w}$$

Finally, what we obtained is a time–frequency representation of these topological measures (Fig. 1, panel d) for each subject and condition, to be used for statistical comparisons.

Note that, as the betweenness centrality measure describes each node performance across the network, it is not possible to represent it as in Fig. 1, panel d, where unitary parameters are obtained from the entire network. Therefore, we represent this measure using scalp topographical maps referring to a specific time–frequency point (see Fig. 2, panel (c) and (f)).

2.6. Statistical analysis

Statistical analysis assessed for differences in the time–frequency data of the global topological parameters. A nonparametric bootstrap-based t -test method from the Resampling Statistical Toolkit was used. This package is part of EEGLAB software and contains a set of functions for inferential statistics using resampling methods (available at <http://scn.ucsd.edu/repos/software/eeglab/functions/statistics/>). The number of surrogate data copies to use in the bootstrap mode estimation was set to 10,000. An FDR correction for multiple comparisons (Efron, 2004) (at $q = 0.05$) was performed. Only clusters of significant fdr -corrected p -values composed of more than 2 time–frequency points were considered to reflect significant differences between conditions.

3. Results

3.1. Behavioral results

In order to evaluate if the correct responses to the different morphosyntactic conditions are different or not between the two groups, a balanced two-way ANOVA was performed. Results showed similar behavioral performance (all $p > 0.1$), guaranteeing that highly proficient late L2 learners performed in the on-line task similarly to the Spanish monolinguals (Table 1).

3.2. Complex network analysis results

3.2.1. Measures of integration (E_{glob} and L)

A first analysis assessed for differences between groups in the Agreement ‘baseline’ condition. No statistically significant differences emerged in the topological parameters E_{glob} and L . This

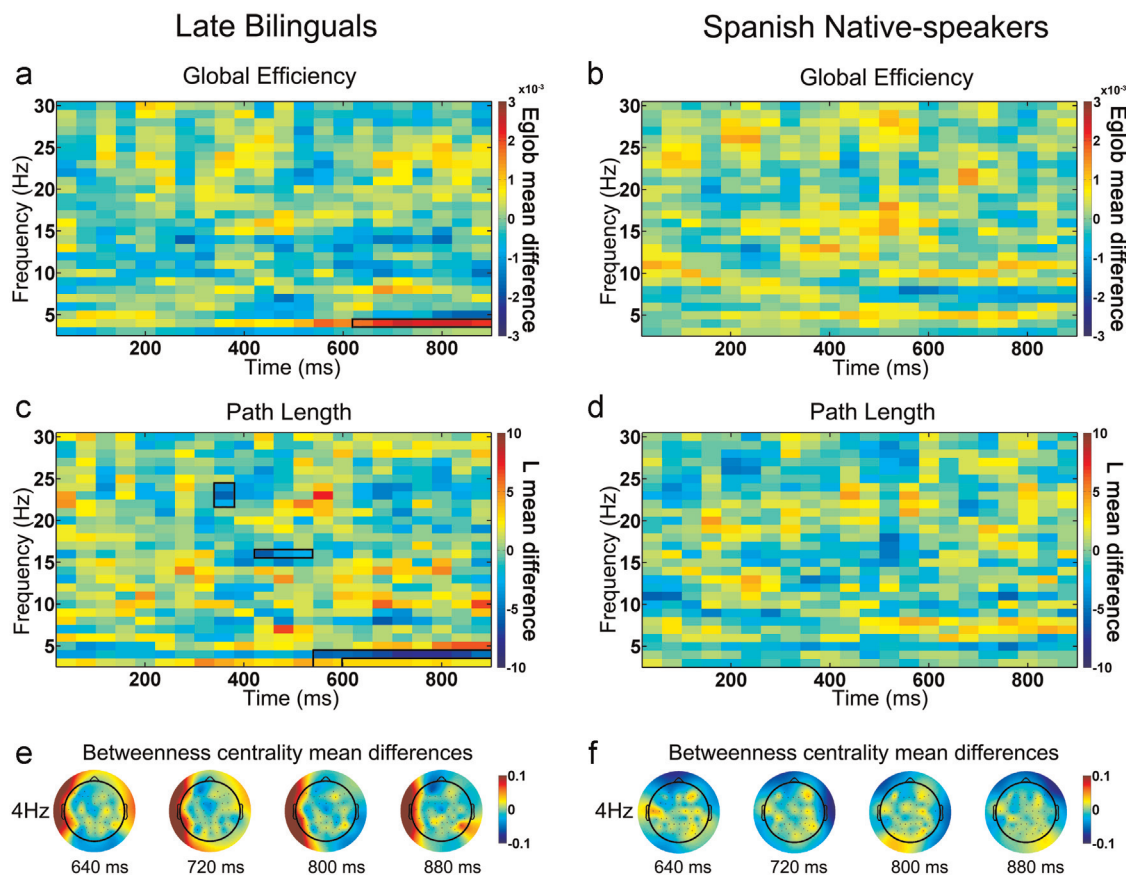


Fig. 2. Mean differences between the Agreement and Gender Disagreement conditions for each group related to three topological features. The left column corresponds to the Late Bilingual group and the right column to the Spanish Native speaker group. Time range is from 40 ms to 880 ms after the target (noun word) onset. The color scale represents the mean difference, i.e. the subtraction of the topological feature average corresponding to the Agreement condition minus the average corresponding to the Gender Disagreement condition. Red color indicates higher values for the Agreement condition while blue indicates higher values for the Disagreement condition. Black contour lines outline time frequency clusters that show statistically significant differences ($p_{FDR-corr} < 0.05$). (Panels a,b) Time–frequency maps of global efficiency mean differences. (Panels c,d) Time–frequency maps of characteristic path length. (Panels e,f) Scalp topographical distribution of the betweenness centrality corresponding to the 4 Hz activities at four different time points (640, 720, 800 and 880 ms). (For the interpretation of references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Mean percentage and standard deviation (SD) values of correct responses for each group in the experimental conditions.

	Late bilingual group	Spanish native-speaker group
Agreement	94.6 (3.5)	94.6 (3.2)
Gender Disagreement	93.1 (3.1)	95.6 (1.8)

indicates that both groups have similar patterns, in terms of information flow, when reading a correct sentence.

A second analysis assessed for differences between groups in the Gender Disagreement condition. Statistically significant differences ($p_{FDR-corr} < 0.05$) emerged in E_{glob} at 8 Hz in a time window from 600 to 760 ms and in L at the same 8 Hz frequency from 680 to 760 ms after the target onset. These consisted in lower global efficiency and shorter path lengths for the Late Bilingual group as compared to the Spanish Native-speaker group. This indicates differences between these groups in the patterns of information flow when processing sentences in the Gender Disagreement condition.

We then compared the Agreement and Gender Disagreement conditions inside each group. Fig. 2 (panels a, b, d and e) shows the time–frequency representation of the mean differences between conditions (Agreement minus Gender Disagreement) for the topological features E_{glob} and L in each group. There are differences

between conditions in the topological parameters for the Late Bilingual group but not for the Spanish Native-speaker group, where the patterns are similar.

For the Late Bilingual group, in the case of E_{glob} (Fig. 2 panel a), the significant differences consisted in a lower global efficiency for the functional networks corresponding to the Gender Disagreement as compared to the Agreement condition. This is denoted by the positive (red) values in the 4 Hz frequency, for a time window from 640 to 880 ms. In the case of the L measure (Fig. 2 panel b), the negative (blue) values in the clusters containing significant differences denote longer path lengths (i.e. less compactness, slower propagation) for the functional networks related to the Gender Disagreement condition. This pattern of results is not surprising, since E_{glob} and L are two related measures and longer path lengths are associated with decreased global efficiency. The main differences in L values are in the frequency of 4 Hz (time window from 580 to 880 ms) but also in 3 Hz, 16 Hz (440–520 ms) and a frequency range from 22 to 24 Hz (380 ms).

3.2.2. Node centrality (Betweenness centrality)

We assessed for differences in the betweenness centrality measure only in those comparisons and time–frequency points that were significantly different in the measures of integration.

Betweenness centrality of all nodes was compared between groups in the Gender Disagreement condition at 8 Hz at time points corresponding to 680, 720 and 760 ms. A two-sample t -test

1 showed that the measures were significantly different ($p < 0.05$)
 2 between groups at electrodes CZ, TCP1, T6 (more indispensable for the
 3 Late Bilingual group) and O2, C5A (more indispensable for
 4 Spanish native speakers).

5 Betweenness centrality of all nodes was also compared be-
 6 tween the Agreement and Gender Disagreement conditions for the
 7 Late Bilingual group, at 4 Hz frequency at the time points 640, 720,
 8 800 and 880 ms. A paired-sample t -test showed significant dif-
 9 ferences between conditions ($p < 0.05$) at electrodes C1, CZ, CZA,
 10 T3L, C3A (more indispensable for the Gender Disagreement condi-
 11 tion) and P2P, P1 (more indispensable for the Agreement
 12 condition).

13 Fig. 2 panel (e) and (f) shows for both groups the scalp re-
 14 presentation of the relative differences between conditions
 15 (Agreement minus Gender Disagreement) in the betweenness
 16 centrality measure. This illustration is similar to the ERP compo-
 17 nent topography but with the colors representing centrality units
 18 instead of voltage. It allows a visual inspection that suggests a
 19 different direction in the relative change effects and in the topo-
 20 graphical distribution.

23 4. Discussion

25 The present complex network analysis study aimed at assessing
 26 the time-varying topological properties of functional networks as
 27 extracted from EEG recording (Chavez et al., 2010; De Vico Fallani
 28 et al., 2008; Dimitriadis et al., 2010; Valencia et al., 2008) in highly
 29 proficient second language learners and native speakers. Specifi-
 30 cally, we compared English highly proficient late L2 learners of
 31 Spanish and Spanish native monolinguals when performing a
 32 morphosyntactic task involving grammatical gender, a grammat-
 33 ical category which is not present in English. The topological
 34 parameters E_{glob} (global efficiency), L (characteristic path length),
 35 and also the betweenness centrality index were estimated in an
 36 attempt to describe the dynamics of functional cooperation and
 37 interaction of brain areas processing a late-acquired L2 trait not
 38 present in L1, as compared to an agreement (correct sentence)
 39 condition.

40 The results obtained here indicate that in terms of the global
 41 management of information flow, (i) the pattern is similar in late
 42 bilinguals and monolinguals when reading a correct sentence (and
 43 searching for possible incongruencies), (ii) there are different
 44 patterns between late L2 learners and monolinguals when reading
 45 a sentence which is grammatically incorrect due to mismatch in a
 46 morphosyntactic feature (syntactic gender) not present in the first
 47 language, (iii) for the late L2 learners there are differences be-
 48 tween the processing of the correct and the incorrect sentences,
 49 (iv) for the monolinguals there are no differences in the processing
 50 of the correct and the incorrect sentences. In addition, the indis-
 51 pensability of each node (expressed in the betweenness centrality
 52 measure) is dissimilar for the late L2 learners and monolinguals.
 53 Results (i) and (ii) are from direct statistical comparison between
 54 the groups, which is essential when making statements about
 55 different patterns in the time-varying topological properties of
 56 both groups. The fact that the pattern is the same in both groups in
 57 the correct sentence condition is in line with the idea that native-
 58 like processing can be attained (Bowden et al., 2013; Ullman,
 59 2012). However, there are differences between the groups in
 60 processing of the morphosyntactic violation. Curiously, these dif-
 61 ferences are present in the 8 Hz frequency, which belongs to the
 62 alpha frequency band, widely associated to attentional processes
 63 (Brunia, 1993; Foxe et al., 1998; Klimesch et al., 1998; Lopes da
 64 Silva, 1991; Steriade et al., 1990) and it has been suggested that late
 65 L2 learners could devote more attentional resources than L1
 66 speakers when trying to fit a mismatching word into a sentence

context (Newman et al., 2012).

67 Furthermore, for the late L2 learners processing the gender
 68 mismatch condition, we found a lower degree of parallel in-
 69 formation transfer (reflected in the smaller E_{glob}) and slower
 70 propagation between regions (as manifested in the longer L) of the
 71 brain functional networks, as compared with processing standard
 72 sentences. This would suggest that to solve the grammatical in-
 73 consistency, the otherwise more graph-efficient and compact
 74 neural configuration that is evident when processing typical sen-
 75 tences changes to a state in which the neural information is ex-
 76 changed between more broadly distributed regions. Interestingly,
 77 4 Hz belongs to the theta frequency band, which has been sug-
 78 gested in power spectral studies to reflect the retrieval of lexical-
 79 semantic information (Bastiaansen et al., 2008; Davidson and In-
 80 defrey, 2007), as well as verbal working memory load (Bastiaansen
 81 et al., 2002). Thus, it could be that the findings here indicate dif-
 82 ficulties in connecting the currently processed (mismatching)
 83 noun to the (contextual) information that is still active in working
 84 memory (Bastiaansen et al., 2002; Hald et al., 2006). In addition,
 85 due to the parallel of the effects here reported with the timing of
 86 the well-documented P600 component, we could speculate that
 87 we obtained differences at these specific time points because the
 88 differential network configuration is linked, as is the P600 com-
 89 ponent, to controlled (conscious) processing, syntactic integration
 90 or structural reanalysis (Friederici and Kotz, 2003; Hahne and
 91 Friederici, 1999; Phillips et al., 2005). However, further validation
 92 will be needed before positing these claims. We also found dif-
 93 ferences in the beta frequency band, which has been described in
 94 power spectral studies as reflecting effects in processes elicited by
 95 syntactically incorrect sentences as compared to correct ones
 96 (Bastiaansen et al., 2010). Thus, it is possible that the different
 97 information flow here reflected in the beta band could be indexing
 98 difficulties in syntactic integration processes.

99 For the Spanish native speaker group, there is no evidence of
 100 differences in the parallel transfer of information and compactness
 101 of the functional networks between processing of standard sen-
 102 tences and sentences containing a grammatical gender-mis-
 103 matching word. Although this result apparently contrasts with the
 104 LAN and P600 effects observed for this group in the ERP study
 105 (Gillon Dowens et al., 2010), the differences can be explained by
 106 the fundamentally different mathematical underpinnings of both
 107 approaches. In standard ERP analysis, epoch averaging of the time
 108 series filters out most of the oscillatory activity due to differences
 109 in latency from one trial to another, retaining only those activities
 110 that are phase-locked to the event. In the present study, complex
 111 network analysis was performed using a method that emphasizes
 112 the spectral decomposition of single-trial event-related EEG
 113 epochs, in order to examine event-related changes in the phase of
 114 oscillations at specific frequencies. In other words, complex net-
 115 work analysis was carried out on 'induced' activity which is poorly
 116 represented or completely absent in the time domain features of
 117 'evoked' ERPs (Makeig, 1993; Makeig et al., 2004).

118 A speculative but interesting idea that could be addressed in
 119 further studies is that up to some point in development, native
 120 readers could possibly show differential complex brain networks
 121 properties associated to the processing of correct and incorrect
 122 sentences (equivalent patterns to the ones found here in late L2
 123 learners) but then, after years of practice, the brain system to
 124 detect language anomalies is optimized in such a way that it can
 125 perform the same in both cases (typical or anomalous) without
 126 this having important implications in the management of in-
 127 formation flow. Another avenue to explore in further studies could
 128 be the temporal network approach. This promising new perspec-
 129 tive in neural network data analysis (Pan and Saramaki, 2011; Tang
 130 et al., 2010) takes into account that the emergence of a unified
 131 neural process is mediated by the continuous formation and
 132

destruction of functional links over time. Considering the timing of connections and their correlations could provide additional information about network dynamics (see [Holme and Saramaki \(2012\)](#) for a review).

The fact that the effects observed in the present analysis are mostly limited to single frequency bins seems to be related to inter-individual differences and the reduced sample size. This means that the frequency peak for synchronization within the different bands varies across subjects ([Doppelmayr et al., 1998](#)). Individual differences in brain dynamics could be exacerbated here due to age-related factors ([Vysata et al., 2012](#)) (i.e. age range of the participants). In the specific case of the theta band, averaging would cause interactions with the adjacent alpha frequency band ([Klimesch et al., 1998](#)), which typically shows a synchronization pattern opposite to the one in theta band. Further studies which focus a priori on specific frequency bands could benefit by adjusting frequency bands individually ([Pérez et al., 2009](#); [Thut et al., 2006](#)).

One possible limitation of this study is that the present analysis was performed on EEG data in sensor space, which contains some inherent spurious correlation because volume conduction causes the signal at each sensor to be a mixture of blurred activity from different inner cortical sources. Although this caveat does not affect the characterization of the global network topology, accurate inferences about anatomical locations need a source reconstruction of the activity in the cortex ([Chavez et al., 2010](#)). Therefore, future studies using cortical source reconstructions would be desirable ([De Vico Fallani et al., 2010](#); [Weisz et al., 2014](#)). Another limitation refers to the fact that the groups are not matched in the distribution of males/females, which could be a confounding factor, since sex differences have been reported in several neurocognitive aspects of language ([Ullman et al., 2008](#)). However, the ERP data analysis on the original data set ([Gillon Dowens et al., 2010](#)) revealed no significant differences between males and females relevant for the present experiment design.

To summarize, the present study showed differences in the network dynamics that subservise morphosyntactic processing in highly proficient late L2 learners and native speakers, providing new insights into questions previously addressed by analyzing focal brain activity ([Bowden et al., 2013](#); [Foucart and Frenck-Mestre, 2011](#); [Gillon Dowens et al., 2010](#); [van Hell and Tokowicz, 2010](#)). Brain complex network analysis is revealed here as a useful approach in addressing the processing of L2 traits not present in L1. Our results indicate that the functional organization related to the processing of correct and mismatching morphosyntactic features is not conformed the same in late bilinguals as it is in monolinguals. The neural activation pattern is configured differently in highly proficient late bilinguals than in monolinguals when a morphosyntactic language incongruence that does not exist in the native language is presented in the second language.

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