Orthographic Coding: Brain Activation for Letters, Symbols, and Digits

Manuel Carreiras1,2,3, Ileana Quíñones1, Juan Andrés Hernández-Cabrera4 and Jon Andoni Duñabeitia4

1Basque Center of Cognition, Brain and Language (BCBL), Donostia, Spain, 2Ikerbasque, Basque Foundation for Science, Bilbao, Spain, 3Department of Basque Language and Communication, University of the Basque Country EHU/UPV, Bilbao, Spain and
4Department of Psychobiology and Methodology, University of La Laguna, Tenerife, Spain

Address correspondence to Manuel Carreiras, Basque Center on Cognition, Brain and Language (BCBL), Paseo Mikeletegi 69-2, 20009, Donostia-San Sebastian, Spain. Email: m.carreiras@bcbl.eu

The present experiment investigates the input coding mechanisms of 3 common printed characters: letters, numbers, and symbols. Despite research in this area, it is yet unclear whether the identity of these 3 elements is processed through the same or different brain pathways. In addition, some computational models propose that the position-in-string coding of these elements responds to general flexible mechanisms of the visual system that are not character-specific, whereas others suggest that the position coding of letters responds to specific processes that are different from those that guide the position-in-string assignment of other types of visual objects. Here, in an fMRI study, we manipulated character position and character identity through the transposition or substitution of 2 internal elements within strings of 4 elements. Participants were presented with 2 consecutive visual strings and asked to decide whether they were the same or different. The results showed: 1) that some brain areas responded more to letters than to numbers and vice versa, suggesting that processing may follow different brain pathways; 2) that the left parietal cortex is involved in letter identity, and critically in letter position coding, specifically contributing to the early stages of the reading process; and that 3) a stimulus-specific mechanism for letter position coding is operating during orthographic processing.

Keywords: Orthographic coding, fMRI, letters, numbers, symbols

Introduction

Letters, numbers, and symbols are essential elements in our modern information society. Letters are salient arbitrary sign, which are omnipresent in our social environment (e.g., publicity hoardings, shop and street names, newspapers, menus in restaurants, etc.). Digits also have a privileged role (e.g., when paying bills or when using PIN codes for credit/debit cards to pay for goods and services), and symbols such as dollar ($), euro (€) or percentage (%) have become widely used. Everywhere and every day we see and use letters, numbers, and symbols, and we have been trained from very early ages to perceive and manipulate them. Thus, an essential question is how our brain processes these elements, since despite our present continuous exposure to them, they are relatively new in terms of human evolution. Does our brain process the identity of these 3 types of symbolic elements in the same way or differently? Does the brain use the same or different mechanisms for coding the ordering of letters, numbers, or symbols when they are embedded in strings? One specific property of strings of alphanumeric characters is the importance of the relative position of each unit in the string. However, there is still no conclusive answer to the question of how character-in-string position is perceived and computed by the human brain. Despite their clear visual similarity, the combinations “clam” and “calm” represent 2 different meanings. Similarly, 1492 (the discovery of America) and 1942 (World War Two) are 2 significant dates that must be clearly differentiated in spite of their visual overlap.

Not surprisingly, the vast majority of findings about the processing of character-in-string position and identity assignment mainly relates to readable material (e.g., letters or words), and this evidence has increased exponentially in recent years (see Grainger 2008 for review). Letter identity assignment (what are the constituent letters in a given string?) and letter position coding (where are those letters within the string?) are 2 key questions that are mandatory for efficient visual word recognition (e.g., Carreiras, Dunabeitia et al. 2009; Carreiras, Gillon-Dowens et al. 2009; Dunabeitia and Carreiras 2011; Perea et al. 2013). Expert readers are able to distinguish between strings that are highly similar at the visual level (e.g., differentiating “hall” from “halt” and “hall”), but at the same time, they achieve a certain degree of perceptual invariance, so that they are able to recognize letters across different fonts, sizes, and cases and are seemingly unaffected by considerable variation in visual features (e.g., recognizing strings such as “hall” and “HALL” as identical). On the other hand, the perception of the correct location of each individual letter within a string is not carried out in a totally precise manner, in that minimal distortion of the canonical position of the elements does not appear to impact perception dramatically. For instance, a transposed-letter nonword such as “cholocate” is frequently misperceived as the word “chocolate” (Perea and Lupker 2004; Perea and Carreiras 2006). Thus, letter identity and position coding are based on flexible perceptual mechanisms adapted for orthographic processing. However, a number of critical points regarding these mechanisms are still unknown, and our understanding of how the neural architecture processes orthographic (and non-orthographic) material is limited. It is not clear whether the perceptual mechanisms responsible for orthographic processing—letter position and letter identity—are entirely rooted within a domain-nonspecific architecture of the visuo-perceptual system or whether they are partly based on domain-general phylogenetic principles and partly based on orthographic-dependent ontogenetic principles. The current study aims to shed light on this issue by comparing neural responses to character-position and character-identity manipulations.

Some of the most recent models of orthographic coding propose that transposed-letter effects (misperceiving “cholocate” as “chocolate”) reflect position uncertainty, due to the operation of generic noise in the position-coding mechanism of the input (Norris 2006; Gomez et al. 2008) whereas other models (Whitney 2001; Grainger and Van Heuven 2003; Davis 2010) claim that transposed-letter effects are accounted for by
letter-specific position coding mechanisms endowed with a certain amount of positional flexibility. That is, while some models argue that position uncertainty is a general property of the visual system that influences the way in which humans perceive any kind of string of elements, regardless of the type of characters forming the strings, other models specify that letter processing is somewhat different from the processing of other types of objects and so is the perception of the position of the individual units of the letter strings. Therefore, models that assume generic positional noise (the consequence of a general visual property) would predict that transposition effects should be similar for letters, numbers, and symbols, whereas models that assume letter-specific mechanisms of position coding would predict that transposition effects for letters would be to some extent unique.

Empirical evidence in favor of letter-specific mechanisms was recently provided by Dunabeitia et al. (2012), who used the classic version of the perceptual matching task (i.e., participants were asked to judge whether 2 stimuli presented consecutively were the same or different) and recorded participants’ electrophysiological evoked activity. Among the sets of different reference-target pairs, they included letter, digit, and symbol strings that could differ due to the transposition or the replacement of 2 internal characters (e.g., letters: NTDF–NDF, digits: 1754–1574 vs. 1754–1684; symbols: & $<–< &$< vs. &$<–&$<). The authors found larger transposition costs for letters as compared with digits and symbols. In particular, they found a generalized transposed-character similarity effect at around 350 ms post-target onset for all types of characters but critically also found an early transposed-character similarity effect (N1/N2) only for letter strings, mimicking the behavioral data, which showed greater transposition costs for letter strings than for digit or symbol strings (Dunabeitia et al. 2012; see also Massol et al. 2013, for a replication and extension of these findings). These results demonstrate that the tolerance of the human perceptual system to alterations in the order of the characters within strings is not a generic visual mechanism that is insensitive to the type of characters forming the strings, thus directly challenging models that claim for character-nonspecific position coding principles, and supporting letter-specific position coding mechanisms that operate over and above generic visual processes. However, the origin of these differential effects remains unexplained and little is known regarding how strings of different alphanumeric characters and their individual positions are perceived and processed by the human brain. Several studies have suggested a differential (privileged) role of letter strings in neural processing, and thus, the differential effects reported by Dunabeitia et al. (2012) for letter strings as compared with symbol and digit strings may emerge from the specific neural pathway(s) in charge of letter string processing.

In fact, some studies suggest that the processing of different types of alphanumeric characters might follow different neural routes in the brain. Previous neuroimaging studies have reported specific right-lateralized patterns of activation for numerical processing (Dehaene et al. 2003; James et al. 2005; Cantlon et al. 2006), identifying the intraparietal sulcus (IPS) as an area critically involved in this mechanism, both in primates and humans. Other recent fMRI data showed a preference for number strings compared with letter strings in the right lateral occipital cortex and a contrary preference for letters compared with numbers in the left fusiform (Park et al. 2012). In addition, a double dissociation from early moments of processing for words and numbers has been reported by Carreiras et al. (unpublished data) using MEG, so that while word processing follows a left lateralized pathway, visual number processing follows a right lateralized pathway, including right parietal areas. Therefore, the current scarce evidence points to the involvement of different neural pathways in the identification and processing of different types of alphanumeric characters.

One of the goals of the present study is to investigate this issue.

Visual word recognition is subserved by a complex reading network functionally divided into 2 pathways: a left tempororo-occipital ventral stream (i.e., specifically the left ventral occipito-temporal cortical and the left ventral inferior frontal gyrus) and a left tempororo-parietal dorsal stream (i.e., especially the supramarginal, the angular gyri, and the dorsal inferior frontal cortex) (Pugh et al. 2001; Price 2012). It is assumed that the ventral stream sustains fast and fluent reading, allowing automatic mapping from orthography to semantics, whereas the dorsal stream supports a much slower and granular reading style, linking the orthographic form of the words with the semantics via phonological recoding. In the ventral stream, the left fusiform gyrus (where the putative visual word form area lies) has been considered a core region in visual word processing, with a marked preference for letter strings with orthographic information. This region exhibits higher activation to words or pseudowords than to false fonts or checkerboards (Cohen et al. 2002; Binder et al. 2006; Baker et al. 2007; see Dehaene and Cohen 2011 for a review). However, the preferential tuning of this brain area for visual orthographic processing and the idea of functional selectivity is still under debate (Price and Devlin 2003, 2011).

In contrast to the huge number of studies investigating the role of the ventral stream during visual word recognition, the number of studies exploring the dorsal pathway is markedly low. Although some experiments seem to suggest that phonological computation is at work in this dorsal pathway (see Jobard et al. 2003 for a review), other studies suggest that some areas of this pathway are also associated with a coarse-grained orthography-to-semantics mapping. Specifically, parietal and left posterior temporal regions in the dorsal pathway have been linked to the “semantic” reading route, since they show higher activation for familiar words than pseudowords (Fiebach et al. 2002; Binder et al. 2003, 2005). Thus, the specific role of the dorsal pathway in reading is still unclear. Interestingly, some recent findings have also highlighted the role of parietal regions in early stages of visual word recognition, suggesting that these areas contribute to letter-identity processing (Reilhac et al. 2013). These authors asked dyslexic and skilled readers to compare 2 subsequent letter strings that could differ due to the replacement of 2 internal characters (e.g., TSHFL–TSHFL vs. TSHFL–TGHML). They found that the replacement-character condition triggered significantly increased activity in the left superior parietal cortex and the left inferior temporal gyrus and that the activation in these 2 regions was also different for dyslexic and skilled readers. Inferior parietal regions have also been associated with serial, effortful reading in skilled readers, when comparing long vs. short pseudowords (Valdois et al. 2006; Schurz et al. 2010) or stimuli with low bigram frequency in word reading (Graves et al. 2010). In addition, activation of superior parietal regions has been associated with tasks that require multi-element processing, such as the visual attention span task (Peyrin et al.
Thus, parietal areas of the dorsal pathway may be also involved in orthographic coding of letter position and letter identity.

Given the theoretical importance of a better characterization of letter-identity and letter-position coding mechanisms and the similarities and differences in the neural representation for letters, digits, and symbols, the present study was designed to investigate the neural effects of replacements and transpositions of letters, numbers, and symbols. By combining the same perceptual matching task used by Dunabeitia et al. (2012) with fMRI, here we asked 1) whether general letter, symbol, and digit string processing differences emerge as a consequence of the distinct neural pathways recruited during the perception of each of these types of strings; 2) whether transposed vs. replaced items trigger more brain activation; and 3) whether these activation differences for transposition cost occur in the same brain areas for the 3 types of strings. In short, we used a visual string comparison task for letters, numbers, and symbols, so that character position or identity was manipulated through the transposition or substitution of the 2 internal elements within strings. It is important to note that from a methodological perspective, this is a very useful approach to examine the process of letter perception in unreadable consonant strings (i.e., nonwords). In this way, letter-level (pre-lexical) processes can be tapped while minimizing the influence of high-level phonological and semantic processes or word-specific orthographic knowledge. Regarding character identity processing, we expect that while strings of letters should activate left lateralized pathways, strings of numbers should activate mostly right lateralized pathways. There are no clear predictions for strings of symbols except some partial overlap with the network activated for strings of letters, as previously found, and recruitment of semantic areas. If the differential transposition effects shown for letter strings are not the result of a different circuit underlying the processing of letter strings as compared with symbol or digit strings, we should expect similar brain activation of a generalized transposition effect for all types of strings. In contrast, if a stimulus-specific mechanism is at work for letter position coding, as suggested by our earlier studies, we should expect a dissociation of activation in transposition cost for letters, numbers, and symbols. Thus, the present study aims to reveal the neurobiological underpinnings of letter-identity and letter-position encoding.

Materials and Methods

Participants

Twenty-four right-handed healthy subjects (10 females), with ages ranging from 18 to 35 years (mean = 21.58, SD = 3.61), participated as paid volunteers in the study. They were native Spanish speakers and had normal or corrected to normal vision and no psychiatric or neurological records. Handedness was ascertained by an abbreviated Spanish version of the Edinburgh Handedness Inventory (Oldfield 1971). All participants gave their written informed consent in accordance with guidelines approved by the Research Committees of the Basque Center on Cognition, Brain and Language. Decision times from 3 participants were lost due to technical problems with the response device; thus, the reaction time (RT) analyses and the correlation analyses between this behavioral measure and the fMRI data were performed using 21 participants (note, however, that the error data for the whole set of participants were available for the analyses).

Stimuli and Experimental Design

Following the experimental design used by Dunabeitia et al. (2012), participants took part in a single scanner session comprising 3 different event-related design functional blocks, which consisted in a serial presentation of reference-target pairs corresponding to 1 of 3 stimuli categories: digits, meaningful symbols, and letters. The stimulation set consisted of 180 reference-target pairs for each stimulus category. All the stimuli were composed of 2 4-character-long strings and were constructed from a set of 9 elements of each category. Letter strings were drawn from the uppercase version of the following consonants: G, N, D, K, F, T, S, B, and L. Digit strings were drawn from the following numbers: 1, 2, 3, 4, 5, 6, 7, 8, and 9. Symbol strings were drawn from the following characters: %, &, @, $, +, $, <, $, and €.

Each block included 3 different conditions in which the correspondence between the reference and the target was manipulated (see Fig. 1 for a schematic representation of a trial). The target could be either 1) the same as the reference but with the 2 internal characters transposed (‘Different Transposed-character’ condition) or 2) the same as the reference but with the 2 internal characters replaced by others (‘Different Replaced-character’ condition) or 3) the exact repetition of the reference (‘Same’ condition). The proportion of each condition within each stimulus category was 2:1:1, respectively: 90 pairs involved identical reference-target stimuli, 45 pairs differed by a transposition, and 45 pairs differed by replacement.*

All the strings were displayed in white Courier New font on a black background. Each trial started with the presentation of a fixation cross (“+”) in the center of the screen for 300 ms. Subsequently, the reference stimulus was presented for 300 ms immediately followed by the target string that also appeared for 300 ms. To avoid physical overlap between the 2 consecutive strings, the location of references and targets was different while the reference was positioned 3 mm above the exact horizontal center of the screen, the target was positioned 3 mm below. After each reference-pair, a cue was shown for 1100 ms, instructing the participant to press as fast and accurately as possible 1 of 2 buttons when the 2 strings were identical and the other when they were different.

Each participant saw each target string twice, once in which the target was preceded by an identical reference and once in which the target was preceded by a different reference. Two lists were built up so that across both lists, each target appeared in both the “Different Transposed-character” and the “Different Replaced-character” conditions. The lists were counterbalanced across participants. Block presentation order (digits, meaningful symbols, and letters) was randomized across participants, and within each block, the sequence of stimuli was randomly presented to each participant.

Image Acquisition

Scanning was carried out on a Siemens MagneteTrio™, a Tim System 3-T scanner, using a standard thirty two-channel phased-array surface coil (Siemens). In all subjects, BOLD-contrast-weighted echo-planar images for functional event-related scans consisted of 32 axial slices of 3 mm thickness (with 3.75 mm between slices) that covered the whole brain. In-plane resolution was 3 × 3.75 mm, with the following parameters: field of view (FOV) = 1152 × 1152 mm; matrix = 64 × 64; echo time (TE) = 30 ms; repetition time (TR) = 2.7 s with no time gap; flip angle = 90°. The first 6 volumes of each run were discarded to allow for T1 equilibration effects. Subsequently, a MP-RAGE T1-weighted structural image (1 × 1 × 1 mm resolution) was acquired with the following parameters: TE = 2.97 ms, TR = 2530 ms, flip angle = 7°, and FOV = 256 × 256 × 160 mm³. This yielded 176 contiguous 1-mm-thick slices.

fMRI Data Analysis

Data processing and statistical analysis were performed using the Statistical Parametric Mapping SPM8 software package and related tools (http://www.fil.ion.ucl.ac.uk/spm). Functional volumes per subject were processed following a standard processing pipeline. Afterwards, these images were submitted to a fixed-effects analysis, including the 3 blocks corresponding to each type of character (digits, meaningful symbols, and letters) and the 3 experimental conditions (“Different Transposed-character,” “Different Replaced-character,” “Same” conditions).
and “Same” conditions) per block. Statistical parametric maps were generated by modeling univariate general linear model, using for each stimulus type, a regressor obtained by convolving the canonical hemodynamic response function with delta functions at stimulus onsets, and also including the 6 motion-correction parameters as regressors. The stimuli onsets per block include 5 different components. The first one corresponded to the onset of each trial (fixation cross) and was modeled as a single regressor, independently of the experimental conditions. The next 3 corresponded to each experimental condition (“Different Transposed-character,” “Different Replaced-character” and “Same” conditions) and were synchronized with the onset of the target word. In the last component, all the trials associated with incorrect responses were included. Parameters of the GLM were estimated with a robust regression using weighted-least-squares that also corrected for word. In the last component, all the trials associated with incorrect responses were included. Parameters of the GLM were estimated with a robust regression using weighted-least-squares that also corrected for word.

Thirdly, the comparison between the “Different Transposed-character” and the “Different Replaced-character” conditions without a distinction between the types of character allows us to explore whether transposed vs. replaced items trigger different brain activity. Only those peaks or clusters with a P-value corrected for multiple comparisons were considered as significant and reported in the tables of results (Genovese et al. 2002; Nichols and Hayasaka 2005).

A Region of Interest (ROI) analysis was carried out in order to determine whether the activation differences between the “Different Transposed-character” and the “Different Replaced-character” conditions varied as a function of the type of character. The ROIs used were built in MNI space combining a functional and an anatomical criteria such that all voxels: 1) were included in the group-level effect of the contrast “Different Transposed-character” condition > “Different Replaced-character” condition; 2) were connected to a local t maxima; and 3) were included in 1 AAL structural ROI (http://marsbar.sourceforge.net/download.html#aal-structural-rois). This analysis allows us to distinguish between those ROIs showing a differential character-specific transposition cost effect from those exhibiting a general transposition cost effect independent of the character type. Additionally, a series of correlation analyses was performed in order to explore the relationship between the magnitudes of the neural and the behavioral (in the RTs and in the error rate) transposition cost effects for each type of string (letters, digits, symbols). The Pearson’s linear correlation coefficient and the corresponding t- and P-values were reported in the results section. All post-hoc comparison has been corrected using Hochberg correction in order to control the family-wise error rate (Hochberg 1988).

In order to disentangle whether the differential character-specific transposition cost effects derived from the ROI analysis are related to letter-specific position coding mechanisms or to general attentional mechanisms associated with increases of the task difficulty we carried
out 2 different approaches. On the one hand, a 3 (digits, meaningful symbols and letters) × 3 ("Different Transposed-character," "Different Replaced-character"; and "Same" conditions) ANOVA including the behavioral measures (RT and error rates) as covariates was performed (the detailed methodological explanation of this analysis and the corresponding results are included in Supplementary material). This analysis allows us to determine whether the response of some neural regions would be modulated by the task difficulty effects and explore the correspondence between these regions and the regions resulting from the ROI analysis. On the other hand, a series of causal mediation analyses (the series of causal mediation analyses was estimated using a hierarchical multilevel regression model where all repeated measures will be the first hierarchical level and subjects the second one) were performed in order to determine the causal relationship between the different character-specific transposition cost effects at the neural level, estimated using the ROI analysis, and the task difficulty cost effect arising from the behavioral results. This type of analysis quantifies the extent to which the treatment (critical manipulation: "different Transposed-character" and "Different Replaced-character" conditions) affects the outcome (transposition cost effect at the neural response level) through the mediator(s) (behavioral measures: RT and error rates) (Baron and Kenny 1986; Shadish et al. 2001; MacKinnon 2008; Imai, Keele, Tingley 2010; Imai, Keele, Tingley, Yamamoto 2010; Imai et al. 2013). Two different statistical models were tested for each ROI independently: 1) the mediator model, where the behavioral measures are influenced by the manipulation of the treatment and this relationship mediates the causal effect between the treatment and the brain response and 2) the response model, where the behavioral measures and the critical manipulation act as predictors of the brain response (dependent variable). For each model, we estimated the average causal mediation effect (a particular mechanism through the mediator of interest [average causal mediation effect: ACME]) and the direct effect (which includes all other possible mechanisms [average direct effect: ADE]). To improve the statistical power of these estimations, both measures (ACME and ADE) were expressed as a population average estimated through 1000 bootstrap random samples extracted from the data.

Results

Behavioral Results

The critical manipulation in each stimulus category involved only the “different” response trials, including both the “Different Transposed-character” and the “Different Replaced-character” conditions. Thus, the statistical analyses were performed only on these conditions. Trials with incorrect responses and/or RTs below or above 2.5 SDs from the mean were excluded from the latency analysis (2.07% of outliers [standard error = 0.32], with no significant differences across conditions, p > 0.27). Mean RTs and error rates for strings of letters, digits, and symbols in the “Different Transposed-character,” the “Different Replaced-character,” and the “Same” conditions are presented in Table 1, with the corresponding standard error between parentheses. Table 1 also includes the transposition cost effect (RTs/error rates in the “Different Transposed-character” condition minus RTs/error rates in the “Different Replaced-character” conditions) for each type of string. Finally, for the sake of completeness, Table 1 includes mean RTs and error rates for “same” condition. However, they will not be analyzed since they entail comparison and response processes that are different from the “different” conditions.

ANOVAs 3 × 2 on mean response times and error rates were performed using type of character (digits, symbols, and letters) and type of relationship (“Different Transposed-character” and “Different Replaced-character”) as factors (see Fig. 1). For RTs, a significant main effect of type of relationship was found (F<sub>1,23</sub> = 72.35, p < 0.001, ε = 1.0). Additionally, a significant interaction between type of relationship and type of character emerged from this analysis (F<sub>2,46</sub> = 3.30, p < 0.05, ε = 0.98), suggesting that the transposition cost effects were different for the different types of characters. In order to test the source of this interaction, the transposition cost effects for each type of string were contrasted. Planned comparisons demonstrated that the transposition cost effect was larger for letter strings than for number strings (t<sub>23</sub> = 2.68, p < 0.05, p_hochberg < 0.05) and also for symbol strings (t<sub>23</sub> = 3.16, P < 0.005, p_hochberg < 0.01). The difference between the transposition cost effects associated with number and symbol strings was not significant.

The error rate analysis showed significant main effects of type of character (F<sub>2,46</sub> = 10.80, p < 0.001, ε = 0.89) and type of relationship (F<sub>1,23</sub> = 63.05, P < 0.001, ε = 1.0). Similarly to the latency analysis, the interaction between the 2 factors was significant, suggesting that magnitude of the transposition cost differed across stimulus types (F<sub>2,46</sub> = 7.99, P < 0.001, ε = 0.99). Planned comparisons showed that the transposition cost effect was larger for letter strings than for number strings (t<sub>23</sub> = 3.53, P < 0.005, p_hochberg < 0.01). However, while the difference between the transposition cost effect associated with letter strings and symbol strings was not significant, significant differences emerged from the comparison between number strings and symbol strings (t<sub>23</sub> = 3.18, P < 0.005, p_hochberg < 0.01) (see also Supplementary Fig. 1S for the results corresponding to the 3 × 3 ANOVAs). Responses to transpositions are harder and slower than responses to replaced and same conditions, which are fairly similar [see Ratcliff and Hacker (1981) for slower responses for “same” than for “different” responses] (in the current set of data, the “Same” responses were faster than the “Different Transposed-letter” responses but not significantly different from the “Different Replaced-letter” responses. In fact, in the letter condition, the “Same” responses were slightly slower (15 m) but not significantly different from the “Different Transposed-letter” responses. In the case of digits and symbols, “Same” responses were slightly faster than “Different Replaced-character” responses, but in neither of the 2 cases significantly different. Importantly, the perceptual matching task is essentially a discrimination task, so that participants are asked to discriminate between “Same” and “Different” trials. According to Ratcliff (1981) “Same” responses in this task should not be necessarily always faster than the “Different” responses given that the estimated value for

| Table 1 |
|---|---|---|
| Error rates and mean decision times (in ms) for the 3 types of strings with standard error between parentheses |
| Experimental conditions | RTs | Error rates |
| Letters | Same | 738.46 (24.30) | 4.95 (1.01) |
| | Different Transposed character | 776.41 (20.95) | 18.98 (2.73) |
| | Different Replaced character | 723.99 (22.11) | 3.24 (0.80) |
| | Transposition Cost Effect | 52.42 (8.42) | 15.74 (2.25) |
| Digits | Same | 762.62 (24.84) | 3.79 (0.78) |
| | Different Transposed character | 754.77 (22.85) | 10.37 (2.03) |
| | Different Replaced character | 724.06 (24.53) | 3.51 (0.86) |
| | Transposition Cost Effect | 30.71 (8.99) | 6.85 (2.04) |
| Symbols | Same | 746.44 (20.00) | 5.51 (1.13) |
| | Different Transposed character | 775.36 (20.18) | 22.31 (2.79) |
| | Different Replaced character | 750.48 (19.36) | 8.06 (1.48) |
| | Transposition Cost Effect | 24.90 (5.43) | 14.26 (1.91) |

Note: “Transposition cost effect” is the outcome of the subtraction of the values in the Different Transposed-character condition from the values in the Different Replaced-character condition.
discrimination depends on the particular speed-accuracy criterion set by the participant. Thus, by adding a very difficult condition such as in the present experiment (the “Different Transposed-letter” condition), the usual result—that “Same” responses are faster than “Different” responses—can easily be reversed, since this leads to slow “Same” responses, slow difficult “Different” responses, and fast easy “Different” responses. In fact, Ratcliff (1981: Exp. 1) reports slower responses for the “Same” than for the “Different” responses using similar kinds of stimuli).

**Selective Response to Each Type of String (Identity Effect)**

To characterize the functional neuro-anatomical network involved in the processing of each type of string, independently of the position-character manipulation, we extracted the...
effects for letters, numbers, and meaningful symbols separately from the $3 \times 2$ factorial analysis, taking into account only the different trials (the “Different Transposed-character” and the “Different Replaced-character” conditions). We first identified the regions showing significantly different BOLD responses for letters, numbers, and symbols separately, as compared with the fixation baseline condition (Fig. 2, left column). Next, we corroborated the selectivity or increased sensitivity of these regions to the specific type of strings by contrasting in a pairwise manner the stimulus-dependent BOLD responses (Fig. 2, right column).

Letter strings compared with the fixation baseline (although the cross is a symbol, it has been used as baseline because it is used as a fixation point and is commonly used as baseline in many fMRI studies. In any case, the baseline is clearly distinguished from the symbol condition, since the fixation cross was always presented alone and the set of symbols always appeared in strings of 4 units) produced increased responses in a widespread fronto–parieto–temporal network, bilaterally distributed (Fig. 2A). These neuro-anatomical regions included an extensive cluster extending from the posterior portion of the inferior occipital gyrus to the anterior part of the fusiform gyrus, as well as the superior parietal cortex, the superior and inferior frontal gyrus, and the postcentral cortex (see Table 2 for details). Interestingly, while frontal and parietal regions in both hemispheres exhibited higher response rates to letter strings than to number and symbol strings (see Supplementary Table 1S), occipito-temporal regions exhibited a letter-selective posterior-to-anterior gradient only in the left hemisphere (see also Supplementary Fig. 2S). No differences in activation were found between letters, numbers, and symbols in the posterior part of the left inferior occipital cortex. In contrast, the most anterior part of the left fusiform gyrus showed higher responses to letter strings than number and symbol strings (see Supplementary Table 1S).

Number strings showed more activation in the left inferior and the middle occipital gyrus, the right fusiform, the right inferior and middle temporal gyrus, the right inferior and superior parietal cortex, the right supramarginal gyrus, as well as some of the basal nuclei (left pallidum, left caudate, and right and left putamen). However, these brain regions did not show number-selective responses. Although they exhibited higher response to number strings than to letter strings, no differences were found when comparing numbers and symbols (Fig. 2B, Table 2 and see Supplementary Table 1S).

Symbol strings showed increases in the left and right inferior and middle occipital gyrus, the left fusiform gyrus, the right inferior and middle temporal gyrus, the right precentral and the left postcentral cortex, as well as the left and right pars opercularis within the inferior frontal gyrus (Fig. 2C and Table 2). In the pairwise comparisons, symbol strings showed higher activation than letter strings but no differences from number strings in the right inferior temporal cortex. Furthermore, symbols showed similar activation to letters and more activation than numbers in the pars opercularis. Interestingly, symbol-selective activation was found in the right middle temporal gyrus: this region showed more activation for symbol strings than for letter and number strings (see Supplementary Table 1S) (to further confirm that these effects calculated over the “Different” conditions were not influenced by the specific manipulations carried out on those trials, the same analyses were also run on the trials corresponding to the “Same” conditions. Not surprisingly, the results from these analyses mimicked the findings described earlier [see Supplementary Figure 3S]. In fact, the brain network activated for same and different responses is very similar [see Supplementary Figure 4S]).

### Transposition Cost Effect

In order to explore whether replaced- vs. transposed-character stimuli would trigger different brain activation patterns, we first carried out a general $3 \times 2$ factorial design that included the type of character (letters, digits, and symbols) and the type of relationship (the “Different Transposed-character” and the “Different Replaced-character” conditions) as factors. Several regions in 2 different lateralized clusters were identified as showing a significant transposition cost effect (Table 3). The left cluster included the superior and inferior parietal gyrus, and the right cluster included the superior an inferior parietal gyrus and the angular gyrus.

Next, we performed a series of regions of interest (ROIs) analyses on the transposition cost effects (namely, on the differences between the transposed and the replaced-character conditions for each type of string). The 2 clusters identified in

| Table 2 |

<table>
<thead>
<tr>
<th>Hemisphere</th>
<th>Letters vs. baseline</th>
<th>Digits vs. baseline</th>
<th>Symbols vs. baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Region</td>
<td>$x, y, z$ (mm)</td>
<td>No. voxels</td>
<td>$Z$</td>
</tr>
<tr>
<td>Left</td>
<td>Occupal_Inf 42, –70, –4 760 8.84</td>
<td>Occupal_Mid 40, –72, 2 495 8.43</td>
<td>Occupal_Inf 44, –66, –4 1554 10.03</td>
</tr>
<tr>
<td></td>
<td>Occipal_Mid 34, –80, 0 7.88</td>
<td>Occipal_Mid 44, –66, –12 4.27</td>
<td>Occipal_Mid 40, –74, 2 8.27</td>
</tr>
<tr>
<td></td>
<td>Fusiform 36, –48, –20 7.66</td>
<td>Putamen 30, –2, –6 521 5.69</td>
<td>Fusiform 36, –52, –20 7.95</td>
</tr>
<tr>
<td></td>
<td>Postcentral 36, –38, 58 1595 7.98</td>
<td>Caudate 16, –4, 26 471 5.11</td>
<td>Postcentral 24, –42, 72 205 7.54</td>
</tr>
<tr>
<td></td>
<td>Parietal_Sup 28, –48, 68 7.72</td>
<td>Precentral 48, 8, 32 247 5.73</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Frontal_Sup 28, –48, 66 7.54</td>
<td>Precentral 58, 10, 24 202 6.29</td>
<td></td>
</tr>
<tr>
<td>Right</td>
<td>Fusiform 44, –54, –18 378 7.35</td>
<td>Palidum 38, –54, –12 746 5.7</td>
<td>Precentral 54, 8, 32 247 5.71</td>
</tr>
<tr>
<td></td>
<td>Occipal_Inf 40, –66, –14 6.05</td>
<td>Putamen 42, –66, 0 5.39</td>
<td>Precentral 50, 6, 24 5.55</td>
</tr>
<tr>
<td></td>
<td>Postcentral 40, –28, 42 6.8</td>
<td>Temporal_Mid 54, 58, 50 5.21</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Frontal_Sup 34, –6, 62 219 6.6</td>
<td>Temporal_Mid 24, –10, 0 6.05</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Precentral 32, –3, 52 5.45</td>
<td>Supra_Med 46, –66, 4 10.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Frontal_Inf_Oper 56, 12, 30 5.46</td>
<td>Precentral 26, 8, 473 4.75</td>
<td></td>
</tr>
</tbody>
</table>

Note: All the regions reported are significant at the peak level after FWE or FDR correction ($P < 0.05$). $x, y, z$ (mm) = coordinates in MNI space [Evens et al. 1993] of local maxima; $Z =$ $Z$ scores; No. voxels = number of voxels significantly activated inside the cluster belonging to each local maximum; Inf, inferior; Sup, superior; Mid, middle; Oper, opercularis.
the previous analysis were used to build the ROIs by applying an anatomical restriction according to the AAL atlas (http://marsbar.sourceforge.net/download.html#aal-structural-rois). This process resulted in the identification of 5 ROIs in which the transposition cost effect was significant: the left inferior parietal region, the left superior parietal region, the right inferior parietal region, the right superior parietal region, and the right angular region (Fig. 3A). The single-factor analysis (transposition cost effect, 3 levels: letters, digits, and symbols) showed that these effects did not differ from each other in the right inferior and superior parietal cortex and in the right angular gyrus (all P-values > 0.16) (i.e., the magnitudes of the transposed-character effects were similar for letters, symbols, and digits in the right ROIs). In contrast, significant differences were found in the left inferior (F_{2,69} = 5.16, P < 0.01) and left superior parietal regions (F_{2,69} = 3.18, P < 0.05). Follow-up pairwise comparisons showed that the transposition cost effect was larger for letters than for digits (left inferior parietal gyrus: t_{23} = 2.30, P < 0.005; left superior parietal gyrus: t_{23} = 2.17, P < 0.05) and for letters than for symbols (left inferior parietal gyrus: t_{23} = 2.48, P < 0.05; left superior parietal gyrus: t_{23} = 2.11, P < 0.05). The differences between digits and symbols were negligible (all P-values > 0.64) (Fig. 3B).

Finally, we also explored the relationship between the magnitudes of the neural and the behavioral transposition cost effects for each type of string (letters, digits, and symbols) by a series of correlation analyses. We estimated the correlation between the transposition cost effect in the 5 ROIs described earlier and the corresponding behavioral effects for each type of string by considering the effects in the RTs and in the error rates. Importantly, only the correlation between the transposition cost effect in the left superior parietal region for “letter” strings and the corresponding transposition cost effect derived from the error rate analysis for “letter” strings was significant (r_{23} = −0.51, P = 0.02) (see Fig. 3C). No other regions showed significant correlations with participant behavior for any of the types of characters in the critical ROIs (‖r < 0.36 or all r-values < 0.36, P-values > 0.10). This correlation that was exclusively found for letter strings highlights the close link between the magnitudes of the transposition cost effects for orthographic material in the left inferior parietal region and reading behavior. An increased activation for the transposition cost effect in this brain area is associated with a decrease in the magnitude of the transposition cost effect in the error rates. Hence, the recruitment of the left inferior parietal region seems critical for successful letter position coding.

In order to determine whether the differential letter-specific transposition cost effects found for the left parietal clusters are related to letter-specific position coding mechanisms or to general attentional mechanisms associated with increases in the task difficulty, we carried out a series of causal mediation analyses (another piece of evidence showing that left parietal activation cannot be accounted for by general attention mechanisms but is related to letter-specific position coding mechanisms is that this activation remains significant when contrasting all conditions with the baseline, with or without including reaction times as covariates [see Supplementary Figure 5S and Supplementary text]). This type of analysis allows us to identify and/or extract the potential effect of the task difficulty over the causal pathway between the treatment and the brain response. The mediator model is represented by the semi-circle in the causal diagram (Fig. 4), where the causal effect of the treatment (critical manipulation: Different Transposed-character/Different Replaced-character) on the outcome (transposition cost effect at the neural response level) is transmitted through an intermediate variable or a mediator (behavioral measures: RT and error rates). The response model is represented by the triangle, where the behavioral measures and the critical manipulation act as predictors of the brain response.

Both models were tested for the left superior and inferior parietal regions. The effects of RT and error rates as mediator variables were estimated separately, represented by the black and the gray lines, respectively. First, taking into consideration the RT, the causal response effect between the treatment and the brain response outcome was significant for both ROIs. In contrast, no direct significant effect was found between the RT and the brain response outcome. Similarly, for both ROIs, the mediator model effects considering the RT as a mediator variable between treatment and neural response was not significant. The corresponding ACME and ADE are reported in Table 4. In the case of the error rates, similar results were found. The response model shows that while the causal effects between the treatment and the neural response were significant, no significant effects were found between the RT and the neural response. In addition, the mediator model when considering the error rates as a mediator variable between treatment and neural response shows that the neural response is conditioned by the task difficulty (regarding the error rates) only in the left superior parietal region. However, the direct causal effect of the treatment on the brain response is still significant even when the variance in the brain response explained by the influence of the error rates is removed (see the corresponding ACME and ADE values for each model in the Table 4). No significant causal mediator effect was found in the left inferior parietal cortex. These results suggest that the letter-specific transposition cost effects at the neural level found in the left inferior and superior parietal regions are not biased by the task difficulty.

**Discussion**

Taken together, these results show that there are specific brain areas that respond more to letters than to digits and symbols and that letter position coding is primarily supported by specific brain areas that are much less involved in the computation of the position of other types of characters. With regard to the

<table>
<thead>
<tr>
<th>Table 3 Transposition cost effect independently of the type of character</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hemisphere</td>
</tr>
<tr>
<td>Region</td>
</tr>
<tr>
<td>Left</td>
</tr>
<tr>
<td>Parietal_Sup</td>
</tr>
<tr>
<td>Right</td>
</tr>
<tr>
<td>Parietal_Sup</td>
</tr>
<tr>
<td>Angular</td>
</tr>
</tbody>
</table>

Note: All the regions reported are significant at the peak level after FWE or FDR correction (P < 0.05). x, y, z (mm) = coordinates in MNI space of local maxima; Z = Z-scores; No. voxels = number of voxels significantly activated inside the cluster belonging to each local maximum; Sup, superior.
Figure 3. (A) Clusters identified as showing a significant transposition cost effect were projected on the surface of the MNI single-subject T1 image. The 2 clusters depicted at $P < 0.001$ corrected for multiple comparisons. The 5 ROIs obtained by applying an anatomical restriction are represented with different colors: the right superior parietal gyrus.
first issue of interest (i.e., the different neural pathways associated with character identity coding), results showed that the left fusiform gyrus and the left inferior and superior parietal gyri showed increased activation for letter strings as compared with the other types of characters, whereas the pars opercularis in the left inferior frontal gyrus and part of the left fusiform responded equally to letters and symbols, but more to these than to digits. Furthermore, other areas responded more to digits than letters. Thus, the left medial occipital, right pallidum, the right superior parietal gyrus, and the right inferior temporal sulcus showed increased activation for digit strings than for letter strings. However, no regions showed more activation for digits than for symbols. Finally, the same areas that respond more to digits than letters also respond more to symbols than letters, in addition to the right angular gyrus and the right middle temporal gyrus. Thus, these results show that processing of the 3 elements involves the recruitment of different brain areas. With regard to the second issue of interest (i.e., the different neural regions associated with character position coding), the results showed some common effects of transpositions for all types of characters (in the right inferior and superior parietal and in the right angular gyrus), but at the same time differential effects for letters as compared with digits and symbols (with letter-specific effects in the left superior and inferior parietal cortex). Therefore, the 2 major findings of this experiment are the dissociations found for letters vs. digits and symbols, both relative to the identity and position coding processes.

First, with regard to letter identity processing, we found increased activation in the left fusiform and the pars opercularis, replicating previous findings (Price 2000, 2012). A large number of prior studies have emphasized the implication of the left inferior frontal gyrus in the reading network (Price 2000, 2012). For instance, it has been found to be implicated in articulatory phonology (Hoeft et al. 2007). This area is an important hub of the reading circuit, which seems to respond to written words at the same time as the left ventral occipito-temporal cortex (Corniessen et al. 2009; Wheat et al. 2010) and probably exerts a top-down feedback effect on the representations computed in the left ventral occipito-temporal cortex (Woodhead et al. 2012). Interestingly, this area (pars opercularis) did not show differences between letters and symbols but showed higher activation for these 2 types of characters as compared with digits. Thus, we could speculate that some specific processes related to reading (processing elements that carry meaning such as symbols or that are the building blocks of words) could underlie the processing of letters and symbols but not the processing of digit strings to the same extent.

The increase of activation for letters in the left fusiform is in line with massive evidence showing that the occipito-temporal cortex (the putative visual word-form area) is related to skilled reading (see Dehaene and Cohen 2011 for a review). Skilled readers recruit and tune this fast word recognition system (Cohen and Dehaene 2004; Binder et al. 2006), whereas developmental dyslexia is associated with a failure to recruit the occipito-temporal cortex (Richlan et al. 2011). However, while it is generally agreed that the left fusiform plays an important role in the reading circuit, its specific role and the type of computations carried out in this area are still under dispute (Dehaene and Cohen 2011 vs. Price and Devlin 2011). The current results demonstrate that the left fusiform shows more activation for letters than for digits or symbols, thus indicating computation of orthographic processing in this area. Furthermore, in accordance with previous results (Turkeltaub et al. 2003; Callan et al. 2005; Reinke et al. 2008), posterior areas of the left fusiform also show significant activation for symbols and for letters, suggesting that these posterior areas may be involved in the computation of abstract orthographic representations but also representations related to meaning. It is
important to note that isolated letters do not carry meaning in the sense that they do not have specific referents in the world. Strings of consonants formed from arbitrary combinations, such as the ones presented here, are unlikely to carry meaning either, since they do not form words that refer to the world or even pronounceable pseudowords that could be neighbors of existing words. In contrast, some of the symbols used in the present experiment refer to specific meanings like euro, pound, percentage, etc. So, it is quite likely that while strings of consonants do not access semantics, strings of symbols automatically activate some meanings. In fact, probably because strings of symbols evoked abstract semantic representations, they also recruited other areas that have been previously related to semantic processing, such as the right angular gyrus, right superior parietal and the right middle and inferior temporal cortex. Although this hypothesis needs further investigation, these areas have been previously related to various aspects of semantic processing such as such integrating and retrieving semantic information (Binder et al. 2009; Binder and Desai 2011) and top-down predictions of semantic content (Carreiras, Seghier et al. 2009; Brownsett and Wise 2010).

Secondly, we found several brain areas that responded more to digits than letters. Previous fMRI studies contrasting letters and digits showed more activation for letters than for numbers in the left ventral occipito-temporal cortex, but no areas showing more activation for numbers than for letters (e.g., Polk and Farah 1998; Polk et al. 2002; James et al. 2005; Baker et al. 2007; Reinke et al. 2008). Only a very recent study has shown more activation for numbers than for letters in a right lateral occipital area (Park et al. 2012). Using a different task, we were able to see increase of activation for numbers as compared with letters not only in a left medial occipital area but also in other areas such as right pallidum, right superior parietal gyrus and right inferior temporal sulcus. Interestingly, the recruitment of right hemisphere areas for number processing agrees with a recent study using MEG (Carreiras et al., unpublished data) that revealed a whole right lateralized circuit involved in number processing, including right parietal areas, which dissociated very early from a left lateralized network involved in pseudoword processing. The right bias for number processing is not as clear in the present experiment (see Table 2 and Supplementary Table 1S). Thus, future research is needed to investigate this issue.

Thirdly, 2 key findings regarding character position assignment should be highlighted, given their importance for a correct understanding of letter-specific coding mechanisms. On the one hand, we found a clear increase of activation triggered by transpositions in the dorsal pathway. On the other hand, we specifically identified differential activation for letter transpositions as compared with digit and symbol transpositions in a defined area of the brain (namely, in the left parietal cortex). We not only found letter-specific effects of identity processing in the ventral and dorsal streams but also letter-specific effects of position coding in the dorsal stream. Importantly, while similar activation was found for letter, digit, and symbol transpositions in the right parietal cortex, specific differential activation was found in the left parietal cortex for letter transpositions as compared with digit and symbol transpositions. This suggests that there seem to be some common processes for positional computation of elements in strings. This is predicted by models that assume that transposition effects reflect position uncertainty due to the operation of generic noise in the position coding mechanism of the input (Norris 2006; Gomez et al. 2008), as already suggested by the EEG data presented by Dunabeitia et al. (2012). These authors showed a generalized transposed-character effect for letters, symbols, and digits in a relatively late temporal window that was conceived as a P3. However, the specific effects for letter transpositions found in the left parietal cortex suggest that the flexibility mediating the processing of the position of the letters embedded in orthographic strings does not exclusively respond to visual mechanisms influenced by generic (character-nonspecific) noise. In contrast, as hypothesized by Dunabeitia et al. (2012), these data indicate the existence of letter-specific position coding mechanisms, as predicted by some models (see Massol et al. 2013 for discussion). Hence, the current set of data reinforces the view of letter-specific position coding mechanisms, as already anticipated by the letter-specific N1/N2 effects reported by Dunabeitia et al. (2012) in their electrophysiological study. Furthermore, letter-specific position coding mechanisms were also supported by the results of the correlation analysis, showing that only the activation in the left parietal cortex correlated with behavior in letter string processing. Thus, the current data clearly support the view that, even though generic noise could be operating in the input, a stimulus-specific mechanism for letter position coding is also in place during orthographic processing. The transposition effects found in literates but not in illiterates are also consistent with this view (Dunabeitia et al. 2014).

It could be argued that the effects attributed to letter-position coding could alternatively reflect differences in top-down attention between the conditions. However, there are several reasons to believe that this is not the case. Attentional effects according to Corbetta and Schulman (2011) engage mainly a bilateral fronto-parietal network that comprises the IPS and the frontal eye of each hemisphere. However, the effects we report are not localized in the IPS. On
the other hand, a top-down attentional effect would not predict the differences we have found for the 3 types of stimuli. In particular, it would predict more activation for the stimuli that are harder to process (i.e., stimuli that produced more errors and/or longer RTs. However, transposed letter and transposed symbols were equally hard (776 and 775 milliseconds, respectively, and 18.9% vs. 22.3% errors, respectively) and transposed effects in the left hemisphere were only found for letters, not for symbols. In addition, since the attentional account does not distinguish between stimuli type, it would predict similar effects when contrasting transposed symbols with replaced letters or transposed symbols with replaced digits. However, these contrasts do not produce the same effects we reported for transposed vs. replaced letters. In addition, activation in parietal areas remained significant when we paralled-out RT effects. Finally, when causal mediation analyses were performed to determine whether the letter-specific transposition cost effects found in the left parietal clusters were related to letter-specific position coding mechanisms or to general attentional mechanisms associated with increases in the task difficulty, they showed that the letter-specific transposition cost effects at the neural level found in the left inferior and superior parietal regions were not biased by the task difficulty.

To sum up, the current study has demonstrated the preferential role of the left parietal cortex for letter identity and letter position encoding in the early phases of the reading process and that letter identity and letter position processing are not confined to the ventral pathway but further involve the dorsal visual pathway. These findings are consistent with the involvement of parietal areas in perceptual tasks that involve letter identification and suggest that parietal regions may be involved in the earlier stages of visual word processing (Reilhac et al. 2013). In addition, they are consistent with the idea that the left ventral occipitotemporal cortex is not a mandatory neural toll or an obligatory route for reading (Richardson et al. 2011). The dorsal and ventral pathways can cooperate during visual word recognition processes (see Rosazza et al. 2009). In fact, structural connectivity between regions of the 2 pathways (the posterior parietal cortex and the inferior temporal cortex) has been documented (Thiebaut de Schotten et al. 2012), and transposed effects in the left hemisphere were only found for letters, not for symbols. In addition, since the attentional account does not distinguish between stimuli type, it would predict similar effects when contrasting transposed symbols with replaced letters or transposed symbols with replaced digits. However, these contrasts do not produce the same effects we reported for transposed vs. replaced letters. In addition, activation in parietal areas remained significant when we paralled-out RT effects. Finally, when causal mediation analyses were performed to determine whether the letter-specific transposition cost effects found in the left parietal clusters were related to letter-specific position coding mechanisms or to general attentional mechanisms associated with increases in the task difficulty, they showed that the letter-specific transposition cost effects at the neural level found in the left inferior and superior parietal regions were not biased by the task difficulty.

To sum up, the current study has demonstrated the preferential role of the left parietal cortex for letter identity and letter position encoding in the early phases of the reading process and that letter identity and letter position processing are not confined to the ventral pathway but further involve the dorsal visual pathway. These findings are consistent with the involvement of parietal areas in perceptual tasks that involve letter identification and suggest that parietal regions may be involved in the earlier stages of visual word processing (Reilhac et al. 2013). In addition, they are consistent with the idea that the left ventral occipitotemporal cortex is not a mandatory neural toll or an obligatory route for reading (Richardson et al. 2011). The dorsal and ventral pathways can cooperate during visual word recognition processes (see Rosazza et al. 2009). In fact, structural connectivity between regions of the 2 pathways (the posterior parietal cortex and the inferior temporal cortex) has been documented (Thiebaut de Schotten et al. 2012), and resting state connectivity has also been reported between these 2 regions in skilled readers (Vogel et al. 2012), but not in dyslexic individuals (van der Mark et al. 2009). Further studies are required to determine how regions of the 2 pathways (ventral and dorsal) interact to give rise to visual word recognition, since the division of labor between a ventral route involved in orthography-to-semantics processing and a dorsal route involved in orthography-to-phonology-to-semantics seems to be an excessively simplistic hypothesis not supported by the empirical data.

Supplementary Material
Supplementary material can be found at: http://www.cercor.oxfordjournals.org/

Funding
MC was partially supported by grants CONSOLIDER-INGENIO2010 CSD2008-00048 and PSI2012-31448 from the Spanish Government, and by grant ERC-2011-ADG-295362 from the European Research Council. JAD was partially supported by grant PSI2012-32123 from the Spanish Government.

Note
Conflict of Interest: None declared.

References
Davis CJ. 2010. The spatial coding model of visual word identification. Psychol Rev. 117:713.


Norris D. 2006. The Bayesian reader: explaining word recognition as an optimal Bayesian decision process. Psychol Rev. 113:327–357.


