Visual and Task characteristics may explain hemispheric asymmetry in visual word recognition

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Abstract

Previous studies proposed that the left hemisphere (LH) lateralization in English word recognition is because of the LH superiority in language processing. Nevertheless, Chinese character recognition has been shown to be more bilateral or right hemisphere (RH) lateralized and thus is a counter example of this claim. Through computational modeling, here we show that at least two factors other than language lateralization may influence hemispheric asymmetry in visual word recognition: (1) Visual similarity among words, which can be influenced by the ratio between the alphabet size and the lexicon size and the visual similarity among letters: We show that the more similar the words are in the lexicon, the more high spatial frequency (HSF) information is required to distinguish them, and this leads to more LH lateralization (2) The requirement to decompose a word into letters in order to map them to corresponding phonemes in pronunciation: We show that letter identity mapping requires more HSF information than word identity mapping, and alphabetic reading requires more HSF information than logographic reading; this leads to more LH lateralization in alphabetic languages. These two visual and task characteristic factors alone may explain differences in lateralization between English word and Chinese character recognition, without assuming the influence from language lateralization.

Keywords: visual word recognition, hemispheric asymmetry, computational modeling

Introduction

Lateralization in visual word recognition

Words, which surround us ever since our childhood, have been extensively studied in the research on visual recognition. Previous studies have consistently shown a left hemisphere (LH) lateralization effect in visual word recognition in alphabetic languages such as English. A classical right visual field (RVF)/LH advantage in reading English words (or words in alphabetic languages) has been demonstrated first in tachistoscopic recognition (e.g., Bryden & Rainey, 1963) and consistently reported in other word recognition tasks, such as word naming (Brysbaert & d'Ydewalle, 1990) and lexical decision tasks (Faust, Babkoff, & Kravetz, 1995). Data from fMRI studies have shown a region inside the left fusiform area (Visual Word Form Area, VWFA) responding selectively to words (e.g., McCandliss, Cohen, & Dehaene, 2003). ERP studies also show that words elicit a larger N170 in the LH than strings of symbols (e.g., Maurer, Brandeis, & Dehaene, 2005). This RVF/LH advantage in visual word recognition in alphabetic languages has been argued to be because of the LH lateralization in language processing (e.g., Voyer, 1996).

Nevertheless, this claim has been challenged by at least one counter example, that is, the recognition of Chinese characters. In contrast to the RVF/LH advantage in the recognition of English words, the recognition of Chinese characters, a logographic writing system, has been shown to have a left visual field/right hemisphere (LVF/RH) advantage in orthographic processing, demonstrated in tachistoscopic recognition tasks (e.g., Tzeng et al., 1979; Cheng & Yang, 1989). In addition, Hsiao and Cottrell (2009) showed a left side bias effect in Chinese character perception in Chinese readers (experts), but not in non-Chinese readers (novices). This left side bias effect also suggests the RH involvement in Chinese character processing.

As for phonological processing in Chinese character recognition, Weekes and Zhang (1999) reported phonological priming effects on the recognition of phonetic compounds (i.e. characters with a phonetic radical that has information about character pronunciation) when the characters were presented in the RVF/LH but not in the LVF/RH; this effect was not observed in integrated characters (i.e. characters that do not have a phonetic radical; Weekes, Chen, & Lin, 1998). Thus, research on Chinese character recognition has exhibited a LVF/RH advantage for orthographic processing, and a RVF/LH advantage for phonological processing, especially for phonetic compounds. ERP and fMRI studies of Chinese character recognition have also shown a more bilateral or RH-lateralized activation in the visual system than those of English word recognition (e.g., Tan et al., 2000; Liu & Perfetti, 2003), which is consistent with the behavioral data.

The RH advantage in Chinese character recognition has been argued to reflect the RH superiority in handling holistic pattern recognition (Tzeng et al., 1979). Nevertheless, findings in later studies do not support this claim. For example, Cheng and Yang (1989) showed no laterality effect in the recognition of non-characters and pseudo-characters, suggesting that this RH advantage may be related to lexical knowledge of Chinese characters or learning experience. Also, in contrast to Tzeng et al.'s claim, Hsiao and Cottrell (2009) showed a reduced holistic processing effect in Chinese readers compared with non-Chinese readers. Thus, it remains unclear why Chinese character recognition and English word recognition involve different hemisphere lateralization.

Hemispheric processing model

In order to investigate why Chinese character and English word recognition involve different hemispheric lateralization, here we adopt a computational approach, aiming to examine potential factors that may influence hemispheric asymmetry in visual word recognition, since computational modeling approaches enable us to have better control over variables.

Anatomical evidence shows that our visual field is initially split along the vertical midline, and the two visual hemifields are initially contralaterally projected to different hemispheres. In order to examine at which processing stage this split information converges, Hsiao, Shieh, and Cottrell (2008) conducted a hemispheric modeling study of face recognition, aiming to account for the left side bias effect in face perception. They proposed three models with different timing of convergence: early, intermediate and late convergence models (Figure 1). They showed that both the intermediate and late convergence models are able to account for the left side bias effect in face perception, whereas the early convergence model fails to show the effect.

Hsiao et al.'s hemispheric processing model (2008) incorporates several known observations about visual anatomy and neural computation: Gabor responses are used over the input images to simulate neural responses of cells in the early visual system (Lades et al., 1993); Principal Component Analysis (PCA), a biologically plausible linear compression technique (Sanger, 1989), is used to simulate possible information extraction processes beyond the early visual system. This PCA representation then is used as the input to a two-layer neural network (Figure 2).

In addition, the model implements a theory of hemispheric asymmetry in perception, Double Filtering by Frequency theory (DFF, Ivry & Robertson, 1998). The DFF theory argues that information coming into the brain goes through two frequency filtering stages: The first stage involves attentional selection of a task-relevant frequency range. At the second stage, the LH amplifies high frequency information, while the RH amplifies low frequency information. This differential frequency bias in the two hemispheres is implemented in the model by using two sigmoid weighting functions to assign different weights to the Gabor responses in the two hemispheres (Figure 2).

Here we apply Hsiao et al.'s hemispheric processing model (2008) to the modeling of visual word recognition, in order to examine whether visual and task characteristics alone are able to account for the differences in hemispheric lateralization in different languages, without assuming the influence of language processing being LH-lateralized. We introduce our hypothesis below.

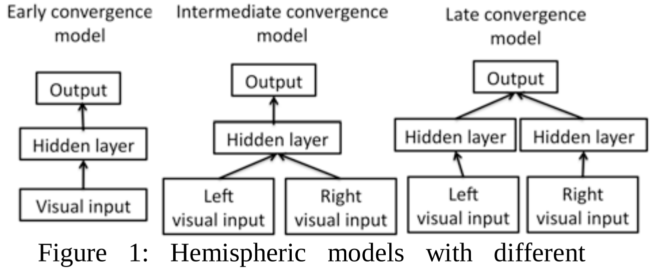

Figure 1: Hemispheric models with different timing of convergence (Hsiao et al., 2008)

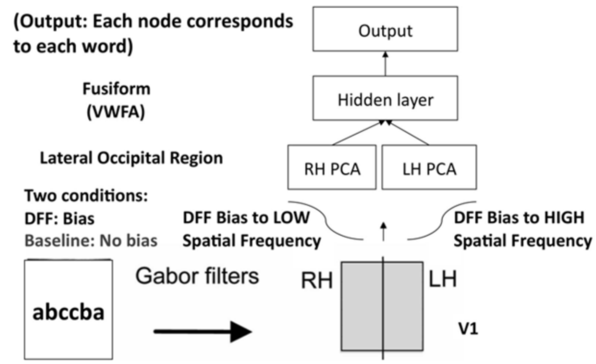

Figure 2: Hsiao et al.'s hemispheric processing model (2008)

Visual and task characteristics of a writing system

Here we test the hypothesis that differences in visual and task characteristics of a writing system alone are able to account for differences in hemispheric lateralization in visual word recognition in different languages. We hypothesize that at least two factors other than language lateralization may influence hemispheric lateralization in visual word recognition:

(1) Visual similarity among words in the lexicon:

The more similar the words look visually in the lexicon, the more high spatial frequency (HSF) information is required to recognize them; this leads to more LH lateralization. We hypothesize that at least two factors may influence visual similarity among words in the lexicon:

(i) Number of letters shared among words in the lexicon: The more letters are shared among words in the lexicon, the more similar the words look visually in the lexicon. This factor is influenced by the ratio between the alphabet size (i.e. the number of letters in the alphabet) and the lexicon size (i.e. the number of words in the lexicon); that is, given a fixed lexicon size, the smaller the alphabet size is, the more number of letters may be shared among the words in the lexicon, and thus the more similar the words look visually in the lexicon.

(ii) Similarity among letters in the alphabet: The more similar the letters in the alphabet look visually, the more similar the words look visually in the lexicon. This factor may be influenced by the number of letters in the alphabet; that is, given a fixed representational space for all possible letters, when we gradually increase the number of letters in the alphabet, it becomes more likely that some letters will look similar to each other (i.e. closer to each other in the space).

According to these two factors, we predict that with a fixed lexicon size, when we gradually increase the alphabet size, the model will first exhibit more and more low spatial frequency (LSF) reliance since the words will share fewer and fewer common letters (factor (i)); when the letters in the alphabet start to look visually similar to each other because of the alphabet size increase, the model will start to exhibit reduced LSF reliance (factor (ii)). In other words, we expect that there will be an inverted-U-shaped curve in LSF reliance/RH lateralization in the model when we gradually increase the alphabet size given a fixed lexicon size.

(2) The requirement to decompose a word into letters in order to map them into corresponding phonemes in pronunciation

Maurer and McCandliss (2007) proposed the phonological mapping hypothesis to account for the difference in ERP N170 lateralization between faces and words: N170 has been found to be larger in the RH compared with the LH in face recognition, whereas in the recognition of English words, it has been found to be larger in the LH compared with the RH. They argued that given phonological processes are typically left-lateralized (e.g., Price et al., 1997; Rumsey et al., 1997), specialized processing of visual words in visual brain areas also becomes left-lateralized. Accordingly, the LH lateralization of N170 may be specifically related to the influence of grapheme-phoneme conversion established during learning to read. According to this hypothesis, this phonological modulation should be less pronounced in logographic scripts such Chinese (Maurer & McCandliss, 2007).

In contrast to the phonological mapping hypothesis, here we hypothesize that the LH lateralization in English word recognition is due to the requirement to decompose a word into letters, without assuming phonological processes being left-lateralized. We test this hypothesis through two simulations. In the first simulation, we contrast two mapping tasks using the same stimuli: word identity mapping and letter identity mapping. In the word identity mapping task, the model learns to distinguish different words, whereas in the letter identity mapping task, the model learns to identify the constituent letter in each letter position of an input word. We expect that the letter identity mapping task will require more HSF information (i.e. LH lateralization) compared with the word identity mapping task[1].

In the second simulation, instead of mapping word image input to either word or letter identities, we model visual word recognition more realistically by mapping them to pronunciations. We use an artificial lexicon with Korean-character-like pseudo-characters as the orthography. Two pronunciation conditions are created: in the alphabetic reading condition, each component (letter) of a character maps to a consonant or vowel in pronunciation systematically, whereas in the logographic reading condition, each character maps to a pronunciation randomly without a systematic relationship between its orthographic components (letters) and the phonemes in pronunciation. We expect that the alphabetic reading condition will require more HSF information (i.e. more LH lateralization) compared with the logographic reading condition.

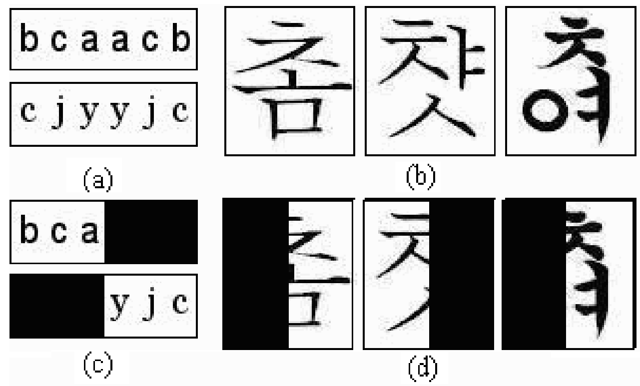

Figure 3: Images used in the current study: (a) palindrome English pseudo-words; (b) Korean pseudo-characters (from left to right, vertical structure, top heavy structure, and bottom heavy structure); (c) & (d) Left and right damaged images of the English pseudo-words and the Korean pseudo-characters

Modeling Method and Results

To test our hypotheses, we applied the intermediate convergence model proposed by Hsiao et al. (2008) to visual word recognition. In the model, the input word images were first filtered with a rigid grid of overlapping 2D Gabor filters (Daugman, 1985) to obtain Gabor responses. At each grid, we used Gabor filters of eight orientations and a fixed number of scales. The number of scales used depended on the task-relevant frequency range, which was determined according to the smaller dimension of the images; the highest frequency scale did not exceed the smaller dimension of the images (following Hsiao et al., 2008). In the current simulation, the dimensions of the two types of images used were 35 x 100 for the English pseudo-words and 70 x 80 for the Korean pseudo-characters (see Figure 3); thus the number of scales for English pseudo-word images was five ($2^5 = 32 < 35$, and $2^6 = 64 > 35$) and that for Korean pseudo-character images was six ($2^6 = 64 < 70$, and $2^7 = 128 > 70$). We applied the Gabor filters to a 5x18 grid of points on each English pseudo-word image, and to a 12x14 grid of points on each Korean pseudo-character image. So each English pseudo-word image was transformed into a vector of size 3600 (5x18 sample points x 8 orientation x 5 scales) while each Korean pseudo-character image was transformed into a vectors of size 8064 (12x14 sample points x 8 orientations x 6 scales).

After obtaining the Gabor magnitudes, two conditions were created: the baseline condition and the biased condition. In the baseline condition (the control condition), Gabor responses in different scales were given equal weights (i.e. no frequency bias), while in the biased condition, we implemented the second stage of the DFF theory by using a sigmoidal weighting function to bias the Gabor responses on the left half word (RH) to LSFs, and those on the right half word (LH) to HSFs (Figure 2). The perceptual representation of each of the left and right half

[1] Note that we reported some pilot data in Hsiao & Cottrell (2009b). Compared with Hsiao & Cottrell (2009b), here we have revised the hypotheses and modeling methods, and presented brand-new and more complete simulations.

words was compressed by PCA into a 50-element representation each (100 elements in total, following Hsiao et al., 2008) [2]. This PCA representation then was used as the input to a two layer neural network, as shown in Figure 2 (see Hsiao et al., 2008, for more simulation details).

We trained our neural network model to recognize the input images until the performance on the training set reached 100% accuracy. The training algorithm was gradient descent with an adaptive learning rate. To test hemispheric asymmetry effects, in contrast to the previous hemispheric models of face and word recognition (e.g., Hsiao et al., 2008, Hsiao & Cottrell, 2009b), here we did not use "chimeric images" (Figure 3(a) & (b)) as a way to give noise to one side of the stimulus in order to test the model's reliance on either the left or right half of the representation. A potential problem in using this kind of chimeric images for words is some letters may have a similar shape as their mirror images (such as 'o' and 'm' in the English alphabet), while others do not; thus these letters will give non-uniform noise distribution over the mirror-image sides of the chimeric words. Here we avoided this problem by using damaged images (Figure 3(c) & (d).) It was made by setting one half of the PCA representation to zero, so that when mapping these damaged images to their identities, only one of the visual hemifields was used for recognition. The left side bias effect thus was measured as the difference between the accuracy of recognizing a right-side-damaged word (carrying LSF/RH information only) as the original word and the accuracy of recognizing a left-side-damaged word (carrying HSF/LH information only) as the original word.

Visual similarity among words in the lexicon:

We first used images of six-letter English pseudo-words to examine how visual similarity among words in the lexicon influences lateralization in visual word recognition. To counterbalance the information carried in the two visual fields, we used palindrome pseudo-words as the stimuli (e.g., Figure 3(a)). We created artificial lexicons with an increasing alphabet size (a-c, a-e, a-g…), and trained the model to learn each lexicon 50 times. In each of the 50 simulations, 26 palindrome words were chosen randomly from all possible combinations of letters in the alphabet to form the artificial lexicon. In the model, each output node corresponded to a word identity.

In the first lexicon with letters from 'a' to 'c', there were 27 possible combinations: aaaaaa, aabbaa, aaccaa, abaaba, abbbba… The randomly chosen 26 words thus looked very similar to one another. When we increased the alphabet size to include 'a' to 'e', the number of combinations became 125, and the randomly chosen 26 words became more dissimilar visually to one another (i.e. the similarity among words decreased). In other words, the larger the alphabet size was, the lower the visual similarities among words in the lexicon were. Here we examined how the model's lateralization changed when we gradually increased the alphabet size.

In the datasets, we used 8 different fonts for each word, with 4 of them used as the training data, and the other 4 used as the testing data (counterbalanced across the simulations). Thus, in both the training and testing datasets, each word had 4 images of different fonts.

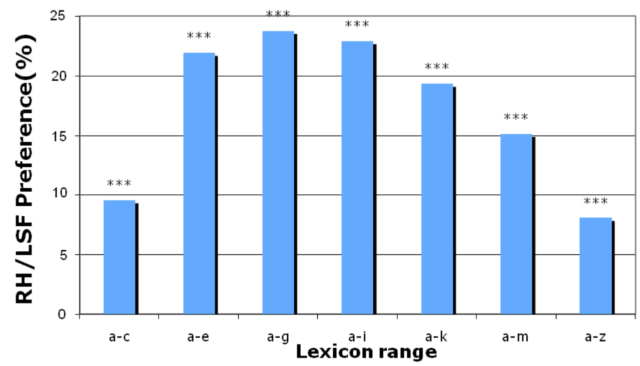

Figure 4: RH/LSF preference in the models trained with lexicons with different alphabet sizes in the word identity mapping task (*p<0.01; **p<0.001; ***p<<0.001).

The results are shown in Figure 4. The RH/LSF preference was defined as the difference in the left side bias effect between the biased condition and the baseline condition; it reflected how much the model preferred the RH/LSF-biased representation over the LH/HSF-biased representation compared with the control condition when no frequency bias was applied (Hsiao et al., 2008). As shown in Figure 4, when the alphabet size was small (e.g., 'a' to 'c'), the model had low RH/LSF preference. When we increased the alphabetic size, the RH/LSF preferences became stronger, and then decreased after the peak at around 'a-g' (i.e., an inverted-U shape in Figure 4).

Thus, the results showed that, when gradually increasing the alphabetic size of the lexicon, the visual similarity among words decreased, and the model relied more on LSFs to distinguish the words. But when the alphabetic size kept increasing, more and more letters with similar shapes were used in the alphabet (e.g., 'c' and 'o', 'b' and 'h', 'm' and 'n'), and the visual similarity among words in the lexicon increased; as the result, the model required more HSFs to distinguish the words.

The requirement to decompose a word into letters

When reading words in alphabetic languages, the readers have to decompose the visual input of a word into its constituent letters/graphemes and map them to the corresponding phonemes. This decomposition may require details of the word image and thus rely more on the HSF information. Here we examined lateralization effects in a letter identity mapping task using the English pseudo-words. Instead of learning to map word images to word identities, the model was trained to map a word image to its constituent letter identities. The output layer of the model

[2] In a separate simulation, we found that using 100 components each made the representation noisier and deteriorated the model's performance.

was divided into 3 parts corresponding to the first 3 letter positions in a word (the end 3 letters were the same as the first 3 since they were palindrome words). The number of nodes in each part was equal to the alphabetic size (see Figure 5).

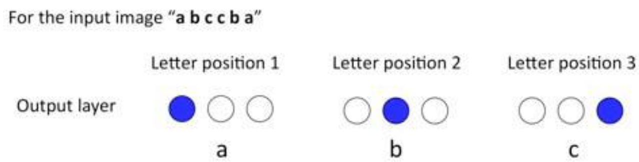

Figure 5: Output layers of the letter-position identity mapping task (Hsiao & Cottrell, 2009b).

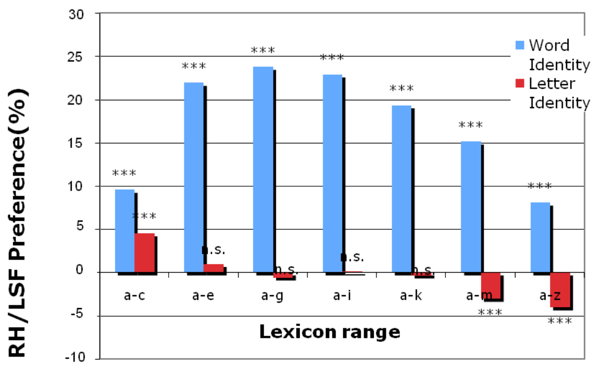

Figure 6: RH/LSF preference in the letter identity mapping task (in red) in the models trained with lexicons of different alphabet sizes, compared with the word identity mapping task (in blue; *p<0.01; **p<0.001; ***p<<0.001).

Figure 6 shows the results. The results showed that compared with the word identity mapping task, the letter identity mapping task required more LH/ HSF information. In addition, in the letter identity task, as the alphabet size increased, the model relied more on LH/HSF information.

In another simulation, we used artificial lexicons with Korean-character-like pseudo-characters to examine hemispheric asymmetry effects in recognizing square-shape characters, and more importantly, to examine hemispheric processing difference between logographic and alphabetic language reading. In this examination, we modeled visual word recognition more realistically by mapping each word input into its pronunciation with a consonant-vowel-consonant structure.

In the datasets, there were also 8 different fonts for each Korean-character-like pseudo-character. Each character consisted of three Korean-alphabet-like letters, arranging in three different structures: vertical, top-heavy, and bottom-heavy (Figure 3(b)). The frequency of each letter appearing in either side of the characters in the lexicon was balanced. In the alphabetic reading condition, each letter systematically mapped to either a vowel or a consonant in pronunciation, whereas in the logographic reading condition, each character mapped to a randomly assigned pronunciation without a systematic letter-phoneme mapping.

Figure 7 shows the results. As shown in the figure, the RH/LSF preference in the logographic reading condition was always stronger than that in the alphabetic reading condition. This result suggests logographic reading requires more LSF information compared with alphabetic reading, and is consistent with the visual word recognition literature showing a more RH lateralization in reading logographic languages such as Chinese compared with alphabetic languages such as English.

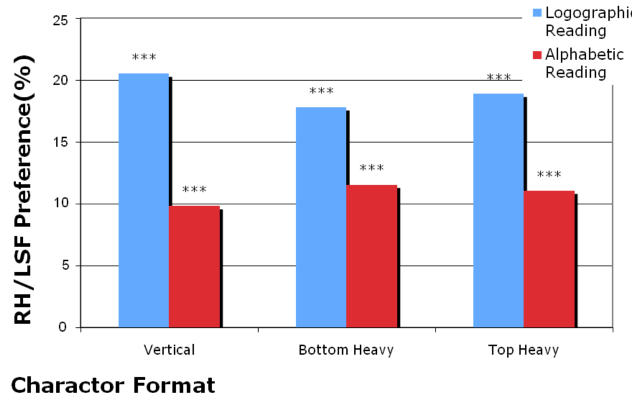

Figure 7: RH/LSF preference in the Korean pseudo-character reading task (*p<0.01; **p<0.001; ***p<<0.001).

Conclusion and Discussion

Visual word recognition in alphabetic languages such as English has been reported to be LH lateralized, and argued to be due to the LH lateralization of language processes. Nevertheless, a RH/LVF advantage has been reported in orthographic processing of Chinese character recognition. In this study, by applying the hemispheric processing model (Hsiao et al., 2008) to visual word recognition, we examined whether visual and task characteristics alone are able to account for differences in hemispheric lateralization in different languages without assuming the influence from language processing being LH-lateralized.

We first showed that visual similarity among words in the lexicon can influence lateralization in visual word recognition. We used artificial lexicons with the same number of words and word length, but with different alphabetic sizes, and trained the model to map word image input to their word identities. The results showed an inverted- U -pattern (Figure 4): When the alphabet size increases, the model initially relies more and more on the RH/LSF information, because words in the lexicon share fewer and fewer common letters and the visual similarity among words in the lexicon decreases. Nevertheless, with further increase of the alphabet size, the model's RH/LSF reliance starts to decrease, because of the increase of visual similarity among letters in the alphabet.

We then showed that the requirement to decompose a word in to its constituent letters can also influence lateralization in visual word recognition. We used the same artificial lexicons but trained the model to perform a letter-identity mapping task instead of the word identity mapping task. The results showed that decomposition of words into letters requires more HSF information and thus results in more LH lateralization. In addition, we used Korean pseudo-characters to examine lateralization differences between logographical reading and alphabetic reading. The results showed that logographical reading requires more LSF information compared with alphabetic reading, and thus results in more RH-lateralization.

The two factors related to visual and task characteristics of a writing system we proposed here are able to account for the lateralization differences between English word and Chinese character recognition. Compared with Chinese, words in the English lexicon may look more similar to one other, because of the smaller alphabet size (only 26 letters) and a much larger lexicon size (more than 20,000 words). In contrast, Chinese has a smaller lexicon size (about 4500 characters for a native speaker), but a much larger "alphabet" (i.e., more than 1000 stroke patterns). In addition, English is an alphabetic language whereas Chinese is a logographic language. Chinese logographic reading may require more LSF information that leads to more RH-lateralization compared with English alphabetic reading, since logographic reading does not require a decomposition of words into letters in order to map them to corresponding phonemes.

In summary, here we show that visual and task characteristics of a writing system alone may account for lateralization differences in visual word recognition in different languages. Specifically, they are (1) visual similarity among words in the lexicon, and (2) the requirement to decompose a word into letters for performing grapheme-phoneme conversion during learning to read.

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