Computational models, educational implications, and methodological innovations: The realm of visual word recognition

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Abstract

This article aims to provide an overview of the current status of visual word recognition research, from the main computational models and their current challenges, to the educational and methodological implications of studies in this field. Visual word recognition is a critical reading process that connects visual sensation and perception with linguistic (sentence, text) processing. For this reason, it has captured the interest of researchers in cognitive science. Importantly, it is particularly easy to model quantitatively and researchers have developed a number of computational models to explain the processes involved. Recent years have witnessed an increasing number of corpora in several languages, including average identification times of thousands of words, allowing virtual simulations of experiments to test the predictions of theoretical models without the recruitment of participants. Nevertheless, despite the advances achieved in the understanding of word processing, these models still have outstanding questions to be answered, such as the role of visual information during word recognition, or how diacritics are represented at the letter level. On the applied side, word recognition research has also contributed to the improvement of educational techniques, such as the development of friendly fonts for different populations, along with methodological innovations in cognitive psychology, such as the use of linear-mixed effects models, Bayesian methods and multi-laboratory approaches.

Keywords: word recognition, reading, lexical decision, methodology, education.

Introduction

> *"Despite appearances, puzzling is not a solitary game: every move the puzzler makes, the puzzlemaker has made before."*
>
> Georges Perec, Life: A user's manual. Preamble

Each encounter with a written word (e.g., mouse) sets in motion innumerable intricate processes. Among them, visual input is analyzed to select the appropriate stored lexical representation among potential competitors in a fraction of a second (e.g., identifying the word mouse, not the similar lexical entries moose, mousse, muse, or house; see Grainger et al., 1989). Thus, the realm of visual-word recognition occupies a strategic domain that bridges the areas of visual perception and sentence (or text) processing.

Critically, the examination of visual-word recognition in cognitive psychology has been considered parallel to the investigation of the cell in biology (see Balota et al., 2006). Several reasons support this comparison. Visual word recognition is particularly tractable for quantitative modeling (see Ratcliff et al., 2004). Indeed, it is possibly one of the areas in psychology with a higher proportion of computational models—in comparison with purely "verbal" theories. Moreover, researchers have at their disposal an increasingly larger number of megabases in various languages that include the average word identification times to thousands of words (e.g., English: Balota et al., 2007; Mandera et al., 2020; Dutch: Brysbaert et al., 2016; French: Ferrand et al., 2010; Catalan: Guasch et al., 2022; Spanish: Aguasvivas et al., 2020).[1] Thus, it is now possible to run virtual simulations of experiments to test the effects of a given factor or the predictions of theoretical models without recruiting participants (e.g., see Perry, 2023; Trifonova & Adelman, 2019). Importantly, in the case of novel experiments, recent research has revealed that online experiments using visual-word recognition tasks such as lexical decision ("is the item a word or not?") produce the same findings as laboratory experiments (see Angele et al., 2023; Ratcliff & Hendrickson, 2021; see also Rodd et al., 2016, for pioneering work of internet-based studies on visual word recognition).

The following sections are not intended to provide a systematic review of the literature on visual word recognition (see Balota et al., 2012; Carreiras et al., 2014; Grainger, 2018, for recent reviews; see also the chapters on this issue in the edited books by Pollatsek & Treiman, 2015, and Snowling et al., 2022). Our goal is to provide a broad perspective on the potential of this field, rather than delving into very specific details. The present paper is organized into four sections. The first section aims to offer a brief—and necessarily subjective—overview of the current state of the computational models of visual-word recognition. Then, in the second section, our focus was on recent research on the interplay between visual and orthographic factors during lexical access, which poses significant challenges for the front-end of current computational models of visual-word recognition. In the third section, we focus on the educational

[1] The readers are referred to http://crr.ugent.be/programs-data/megastudy-data-available for a complete list of megastudies.

implications of studies on visual word recognition, often underexplored. Finally, on the fourth section, we stress the importance of this field when pioneering novel methodological approaches.

A brief historical overview of computational models of visual-word recognition

The basis of the first mainstream of computational models of letter and visual-word recognition originated in the late 50s and 60s of the past century (e.g., letter recognition: pandemonium model, Selfridge, 1959; visual-word recognition: logogen model, Morton, 1969). In the pandemonium model, the recognition of letters was accomplished by a hierarchy of parallel, specialized units—the so-called "demons", each of which extracts a different feature of the letter stimulus. In the logogen model, the recognition of words is achieved through competition of lexical units—the “logogens”, which are activated by the visual input. The logogen that reaches the threshold level of activation represents the identified word.

In the decade of the 70s, in an influential paper, Rumelhart (1977) described the layers of future computational models of visual-word recognition and reading: letter level, letter cluster level, lexical (word) level, syntactic level, and semantic level. The following groundbreaking step was the implementation of the first computational models of visual-word recognition (localist models): the activation-verification model (Paap et al., 1982) and the highly influential interactive-activation model (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982), both having three layers of units: a visual letter feature level, a letter level, and an orthographic word level. While these two computational models were less ambitious than in the initial proposal by Rumelhart (1977), the implementation of layers for syntax and semantics would have been a Herculean task—and even today. The interactive-activation model (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1981), in which excitatory and inhibitory connections operate across and within layers, highlights the importance of interactivity (see Carreiras et al., 2013, for review). When a printed word is presented, the model generates activation at the letter feature level, which in turn activates matching units at the letter and word levels—note that the units at the word level compete with each other (e.g., lexical unit for *mouse* would inhibit the lexical unit for *moose*). The interactive activation model is particularly effective in capturing benchmark effects of word context on letter perception, such as higher levels of letter activation for letters embedded in orthographically legal words compared to those embedded in orthographically illegal pseudowords.

The interactive-activation model was subsequently, in the spirit of nested modelling, at the core of more sophisticated models of visual-word recognition. First, the multiple-read out model (Grainger & Jacobs, 1996) extended the model to the lexical decision task. This model could make “yes” lexical decision responses when the activity of single word units reached a given threshold (the so-called “M” criterion) or when the overall degree of activation in the word layer reached a given threshold (the so-called “S” criterion)—this could explain why words with many orthographic “neighbors” (e.g., *blank*: *bland*, *blink*, *black*, *flank*, among others) produce faster lexical decision times than words with few orthographic “neighbors” (e.g., *harsh*). Furthermore, the multiple read-out model could also respond “no” to pseudowords, via a temporal deadline that was modulated on the degree of activation in the word level, thus capturing the phenomenon that lexical decision times are shorter and more error-prone for pseudowords with few orthographic “neighbors” (e.g., *cliud* [*cloud*]) than with (e.g., *blund* [*bound*, *bland*, *blend*, *blind*, *bold*, *blued*, *blunt*]).[2] Second, the dual-route cascaded [DRC] model (Coltheart et al., 2001) extended the interactive-activation model not only to the lexical decision task—in a roughly similar manner as the multiple-read out model—but also to reading aloud tasks, thus providing a more explicit account of phonological processing rather than relying exclusively on orthographic units (see Frost, 1998, for a review of early research on phonological processing). The “lexical” route in the DRC model was composed essentially of the interactive activation model, and the “sublexical” route included a grapheme-to-phoneme rule system. Third, the Bilingual Interactive Activation model (Dijkstra et al., 1998) extended the interactive-activation model with two layers of words (i.e., one for each language) and an extra layer corresponding to the language nodes—this layer is connected to the two layers of word units (see van Heuven & Dijkstra, 2009, for an extension of this model [BIA+] including a more precise account of phonology and semantics).

In the 1980s, parallel distributed processing—also called connectionist—computational models of visual-word recognition (see McClelland & Rumelhart, 1988) were proposed as an alternative to the above-cited localist models. In parallel models, lexical items were not represented as unified units but rather as a combination of orthographic, phonological, and semantic levels (see Seidenberg & McClelland, 1989). A drawback of these parallel models, unlike localist models, is that they did not perform well when simulating standard word recognition tasks such as lexical decision (see Plaut, 1997). Notably, to overcome this limitation, it is possible to combine the properties from the

[2] Jacobs et al. (1998) further expanded the multiple read-out model by adding a layer of sublexical phonological units (the so-called MROM-p) to the layer of sublexical orthographic units to capture phonological effects (e.g., the pseudohomophone *feal* [/fiːl/, as the word *feel*] producing longer lexical decision times than an orthographic control). In addition, Conrad et al. (2009) expanded the multiple-read out model in Spanish and German by adding an intermediate layer with the word’s initial syllable between the letter level and the word level, thereby capturing the effects of syllable frequency in the lexical decision task (i.e., slower lexical decision times for those words with a frequent initial syllable; Carreiras et al., 1993; see also Álvarez et al., 1993).

localist and distributed models in a single model, as in the connectionist dual-route model proposed by Zorzi et al. (1998).

Importantly, the changes between the computational models in the late 90s and the beginning of the current century were made in response to an empirical phenomenon: the *transposed-letter effect* (e.g., the pseudowords *JUGDE* or *CHOLOCATE* look very similar to their base words *JUDGE* and *CHOCOLATE*), which posed problems for the family of interactive-activation models (e.g., see Andrews, 1996; Perea & Lupker, 2003, 2004; Schoonbaert & Grainger, 2004). In the orthographic coding scheme of the above-cited models, the pseudowords *JUGDE* and *JUPTE* would be orthographically equal to *JUDGE* (i.e., they share the position of three letters out of five). However, the empirical evidence conclusively revealed that transposed-letter pseudowords like *JUGDE* are more easily confusable with their base word than replacement-letter pseudowords like *JUPTE* (see Perea et al., 2023, for review).

One option to capture the transposed-letter effect in the family of interactive-activation models was adding some perceptual uncertainty when encoding letter position. That is, the letter D in *JUGDE* would activate not only the fourth letter position but also the neighboring positions. This is one of the basic ideas behind the latter implementation of several computational models of visual word recognition: the overlap model (Gomez et al., 2008), the spatial coding model (Davis, 2010), and the Bayesian reader model (Norris et al., 2010). Notably, the idea of perceptual uncertainty when encoding letter position also applies to other visual objects, thus capturing transposition effects for digits (e.g., García-Orza & Perea, 2010). Another option chosen by other modelers to capture the flexibility of letter order in words was to add an intermediate layer of "open" bigrams between the letter and word levels, as in the open-bigram model (Grainger & van Heuven, 2003) and the SERIOL model (Whitney, 2001). In the family of open-bigram models, *JUGDE* is orthographically similar to *JUGDE* because they share all "open bigrams" (e.g., *JU, JG, JD, JE, UG, UD, UE, GE, DE*) except one (*GD* for *JUDGE* and *DG* for *JUDGE*).

An advantage of open-bigram models over perceptual uncertainty models of visual word recognition is that they can easily accommodate the presence of stronger transposition effects for letters than for other visual objects (e.g., digits, symbols) (Massol et al., 2013; see also Fernández-López et al., 2022b; Massol & Grainger, 2022). However, a strong version of open-bigram models cannot capture the transposition effects for a series of digits or symbols—or the transposition effects that occur in preliterate readers (see Fernández-López et al., 2022a). Thus, it is sensible to assume that both components, (1) positional noise, common to all objects, and (2) an orthographic component specific for written words, are responsible for the flexibility of letter position in words (see Marcet et al., 2019, for discussion). Indeed, a number of other recent computational models of visual-word recognition have proposed hybrid mechanisms, including both positional noise and open-bigrams (e.g., LETRS model: Adelman, 2011; overlap open-bigram model: Grainger et al., 2006; dual-route model: Grainger & Ziegler, 2011).

Overall, researchers in visual word recognition have at their disposal many computational models that can help them run crucial experiments in scenarios in which the models make different predictions. Notably, some of the implemented models are easy to use. The best instance is probably the windows-based implementation of the Spatial Coding model (Davis, 2010).[3] Furthermore, it is worth noting that there is freely-available computer software for modeling visual-word recognition: EasyNet (see Adelman et al., 2018). Specifically, EasyNet allows users not only to implement the above-cited computational models of visual word recognition but also to implement newer models of visual-word recognition.

Having said this, the above computational models still have important limitations in their front end—let alone higher-level processing (e.g., from morphology to syntax and semantics). For simplicity, we will outline two issues that are currently attracting attention in the field: the role of visual information during visual word recognition and how diacritics are represented at the letter level. These issues will be the focus of the following section.

Limitations of the front-end of current computational models of visual-word recognition: The role of visual information, the Anglocentrism of the letter level, and beyond

Models of visual-word recognition commonly assume that abstract representations drive the process of lexical access. In the initial moments of word processing, visual information (size, font, color, etc.) is mapped on resilient letter units that, in turn, are combined into word units (e.g., see Dehaene et al., 2005, for a hierarchically neurally-inspired model). Empirical evidence supports this assumption. For instance, masked priming studies have shown that the time course of identifying the target word, like *ALTAR*, is very much the same when preceded by the prime *altar* or the prime *ALTAR*. Indeed, the only difference occurs in early time windows that are associated with the featural overlap between the prime and the target (e.g., N/P150), but not in the later components that are associated to orthographic or lexical-semantic processing (e.g., N250 or N400; see Vergara-Martínez et al., 2015; see Grainger & Holcomb, 2009, for a review

[3] This model is available at available at http://www.pc.rhul.ac.uk/staff/c.davis/SpatialCodingModel/

of ERP research on visual word recognition; see also Gomez & Perea, 2020, for similar evidence at the behavioral level with Grade 2 and Grade 4 children).

Likewise, the visual letter similarity effects that have been reported in masked priming experiments (e.g., *obiect* facilitates *OBJECT* more than the control *obaect*; *docurnent* facilitated *DOCUMENT* more than *docusnent*; Marcet & Perea, 2017, 2018a) have their origin at early time windows and vanish in later components (e.g., N400; see Gutierrez-Sigut et al., 2019, for ERP evidence). Similarly, in unprimed lexical decision experiments, pseudowords like *viotin* (which are formed by replaced the letter "*l*" from *violin* with the visually similar letter "*t*") or *viocin* (where the letter "*l*" from *violin* is replaced with the visually dissimilar letter "*c*") produce similar response times, error rates, and ERP waves (see Gutierrez-Sigut et al., 2022; Perea & Panadero, 2014; Perea et al., 2022).

However, as often happens in psychological science, visual-word recognition may be better conceptualized as consisting of various codes. Thus, it would not be surprising that one of the access codes may retain visual information under some circumstances. For instance, Pathak et al. (2019) found that misspelled logotypes produced more errors in lexical decision experiments when the misspelling involved a visually similar letter (e.g., *amazom*; original word: *amazon*) than when it involved a visually dissimilar letter (e.g., *amazot*; see Figure 1). Notably, this same pattern arises with plain brand names (i.e., written in Times New Roman font; Perea et al., 2022). This latter finding implies that the brand name per se (with no other graphical information from the logotype) retains some visual information, presumably because they are often presented in an archetypical format with little variations. Likewise, individuals with presumably less stable abstract representations, such as deaf readers or individuals with dyslexia show some visual letter similarity effects with misspelled common words (e.g., more errors to *viotin* than *viocin*) in scenarios where normotypical readers do not show any differences (see Gutierrez-Sigut et al., 2022; Perea et al., 2016, 2022).

Figure 1. Example of logotypes such as those used by Pathak et al. (2019). On the left, there is the original logotype, whereas on the center and the right are the misspelling with a visually different and a visually similar letter, respectively (adapted from Baciero et al., 2021)

Altogether, these findings suggest that, while abstract representations are the main force behind lexical access, visual information may be retained (and used) at various stages in some special cases (see Carreiras et al., 2013, for a similar claim). Therefore, future implementations of models of visual-word recognition should provide a more accurate account of the interplay between visual vs. abstract codes during lexical access.

Another limitation faced with current models of visual-word recognition is their Anglocentrism. The letter level of the models cited in the previous section was designed for the 26 letters of the English orthography. While one can readily run simulations on EasyNet (or any of the above-cited models) with English materials, most alphabetic languages contain diacritical letters. In the Latin alphabet, the diacritics are placed on some letters to adapt the languages to their specific nuances. For instance, in German, the diacritics of the vowels *a*, *o*, and *u* reflect three phonemes that did not exist in Latin language, from which the orthography was derived. As such, one might argue that *ä*, *ö*, and *ü* should be reflected in separate letter units than *a*, *o*, and *u*. This was the logic in the German adaptation of the DRC model by Ziegler et al. (2000; see also Hutzler et al., 2004).

In contrast, in languages like Spanish, acute accent marks do not alter phonemic information but rather serve to indicate the stressed syllable under some norms—or as a mark to distinguish homonyms in monosyllable words (e.g., *él* [he] vs. *el* [the]). In this scenario, there is no reason why the letters *á* or *a* would be represented separately in the mental lexicon (Perea et al., 2020) and prior simulations with the interactive-activation model in Spanish have encoded the letter *á* as if it were the letter *a* (e.g., Conrad et al., 2010). Indeed, there is empirical evidence for a language-dependent dissociation for diacritical and non-diacritical letters, depending on their function in the language (see Labusch et al., 2023; Marcet et al., 2022; Marcet & Perea, 2022; Perea et al., 2022, for evidence in French, Catalan, Spanish, and German, respectively). For instance, the omission of diacritics in German has a sizeable reading cost during word recognition—compared to the intact words, whereas the omission of diacritics in Spanish has only a minimal reading cost (see Marcet et al., 2021; Perea et al., 2022).

Thus, one challenge for modelers is how to implement a letter level including diacritical letters. For instance, how can we add the letter *ñ* in the letter level of the models? The issue is that the Rumelhart and Siple (1974) font, implemented in the family of interactive-activation models included in EasyNet, is a matrix that does not easily allow for a simple modification (see Figure 2). Things are even more complicated given that diacritics may occur, in different forms, above the letter (e.g., *č* vs. *ć* in Serbian), below the letter (e.g., *ç*), or even across the letter (e.g., the letter *Ł* in Polish).

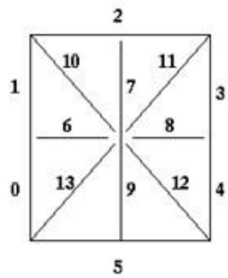

Figure 2. Letter matrix in the Rumelhart and Sipple (1974) font.

One potential way out of the issues regarding the impact of visual letter similarity effects and the intricacies of encoding diacritical letters in the word recognition system is to move from the classical approach (i.e., using levels of letter features, abstract letters, and word units) to modeling visual word recognition from another angle. In recent years, a number of modelers have implemented models of visual-word recognition based on convolutional neural networks, which are type of deep learning neural network that is commonly used in computer vision (e.g. in image classification or object detection). The idea is that these models can automatically and adaptively learn spatial hierarchies of features from input images without explicit letter levels. Critically, as shown by Hannagan et al. (2021), a recent implementation of convolutional neural networks on the basis of myriads of word images of varying letter case, font, and size can simulate many benchmark phenomena in the literature of visual-word recognition, and even the impact of purported brain lesion. In the same lines, Yin et al. (2023) found that models of visual word recognition based on convolutional neural networks provide an excellent account of the masked form priming effects reported in the Adelman et al. (2014) megabase. Indeed, the fits were as good as the better-fitting classical models of visual-word recognition. One notable challenge for these models, however, as Bowers et al. (2022) have noted, is that these networks fail to capture many basic phenomena related to vision (e.g., the manner these networks classify objects [and perhaps letters] are very different from that of humans). Thus, at this moment, it is unclear whether the excellent performance of convolutional neural networks when dealing with written words reflects the human brain's underlying processes.

We acknowledge that a fully comprehensive computational model of visual word recognition would face many other potential challenges. For instance, the interplay in the lexical representations in the bilingual lexicon (e.g., Casaponsa & Duñabeitia, 2016; Commissaire, 2022), the role of morphology (e.g., Lázaro et al., 2021), the role of emotional words during visual-word recognition (see Hinojosa et al., 2019), the role of the writing script (e.g., non-alphabetic; see Li et al., 2022), individual differences (Gómez et al., 2021; Perfetti, 2012), or the emergence and development of the lexical entries in children (e.g., see Castles et al., 2007). Furthermore, there are other relevant factors that the future computational models of visual-word recognition need to account for, including age of acquisition (i.e., those words that are learnt earlier can be processed more efficiently; e.g., see Izura et al., 2009; Juhasz, 2005) or word prevalence (i.e., the proportion of individuals that know a given word [e.g., via crowdsourcing studies] is associated with faster word identification; see Brysbaert et al., 2016).

While an analysis of these important topics would go beyond the scope of the current review, what we should note regarding this last issue is that computational models of visual-word recognition have generally focused on a "static" mode in a normotypical skilled adult readers, rather than in a dynamic process of word learning. For instance, word-frequency is often assumed to be a static, fixed parameter for each word unit in these models (e.g., high- and low-frequency words differ in their so-called "resting levels" in the family of interactive activation models). However, recent research has shown that the number of context that a word is encountered (i.e., contextual diversity) is a more powerful predictor than word-frequency per se (see Adelman et al., 2011, for evidence with adult readers; see Perea et al., 2013, for evidence with developing readers; see Caldwell-Harris, 2021, for review). Of note, while word-frequency and contextual diversity are highly associated (i.e., higher frequency words usually occur in many contexts), the brain signature of each factor is different (see Vergara-Martínez et al., 2017; see Jones et al., 2012, for a dynamic model of word learning based on the principles of contextual diversity). Thus, future computational models of visual-word recognition should have a more dynamic character, including learning new words, presumably via different contexts following the principles stated by Jones et al. (2012).

Another issue that deserves some comment is to what degree the mechanisms that underlie word recognition in the visual modality also underlie the process of word recognition in the tactile modality, as the other sensory modality in which reading is possible. A series of recent experiments with braille readers, Baciero et al. (2022, 2023) have shown that the differences between the tactile and visual modalities appear to be quantitative rather than qualitative. For instance, as also occurs with sighted readers, braille readers show transposition effects with adjacent positions (e.g., *JUGDE* being confusable with *JUDGE*). The difference is that, unlike sighted readers, braille readers do not show transposition effects with non-adjacent letter positions (e.g., *CHOLOCATE* not being confusable with *CHOCOLATE*; see Baciero et al., 2022). Baciero et al. (2022) argued that the differences in scope of the transposed-letter effect are due to the nature of the sensory input of words (i.e., serial for braille readers and [mostly] parallel in sighted readers).

Finally, those readers not familiar with the field of visual-word recognition may wonder whether this research has real implications for normal reading or in educational (or applied) settings. While we devote a discussion of the educational implications in the next section, we should stress that the main phenomena found in visual word recognition tasks (when measuring response times and accuracy) have been easily generalized to the paradigms of sentence reading (when measuring eye fixation durations). The list includes the effects of word-frequency (Rayner & Duffy, 1986), contextual diversity (Plummer et al., 2013), neighborhood frequency (Perea & Pollatsek, 1998), letter transposition effects (Johnson et al., 2007), visual letter similarity (Marcet & Perea, 2018b), orthographic priming (Williams et al., 2006), phonological priming (Pollatsek et al., 1992), semantic priming (Schotter et al., 2014), letter rotation (Fernández-López et al., 2021c), among others. Indeed, the lexical processing system in recently implemented computational models of eye movement control in reading, such as OB1-Reader (Snell et al., 2018) and Über-Reader (Reichle, 2021) are associated with core principles of computational models of visual-word recognition. For instance, when encoding letter position, OB1-Reader takes the ideas of open bigrams, whereas Über-Reader shares the views of position uncertainty.

Educational implications of research in visual-word recognition

The above sections examined the theoretical side of research on visual-word recognition. Importantly, research in this field may also have an applied side, specifically at an educational/developmental level. When we identify a word, we need to encode letter position (if not, we would not distinguish *stressed* from *dessert*) and better readers encode letter order more accurately than worse readers (see Gómez et al., 2021; Pagán et al., 2021). Similarly, we need to encode letter identity (given that we can distinguish *rose* from *nose*) and the easiness with which we do this depends on the font difficulty (see Rayner et al., 2006), especially for those with reading difficulties (see Bachmann & Mengheri, 2018). It is likely that the ability to encode letter order and identity is recycled from object recognition in the brain (see Dehaene & Cohen 2007). In a sample of preliterate children, Fernández-López et al. (2021a) found that scores on a subtest of sequential auditory memory and visual discrimination of the BIL battery for pre-literate children (Sellés et al., 2008) predicted letter position encoding skills. While further research is necessary (e.g., separating the specific components of the sub-batteries or using other perceptual tests), this finding suggests that it is possible to identify very early (i.e., before acquiring literacy), potential reading deficits via tests measuring perceptual and cognitive components—note that there is a specific deficit at encoding letter position (letter position dyslexia; see Kohnen et al., 2012, for evidence in English). We must keep in mind that dyslexia is a deficit whose nature is when encoding sequences of letters or words rather than on comprehension *per se*. That is, the difficulties of dyslexic children when reading are just because the deficit at the word level spills over during reading (see Gabrieli, 2009, for review).

Another avenue in which research of visual-word recognition has an educational side is designing fonts to help special populations when reading. For instance, a number of studies highlighted the need for dyslexic-friendly fonts to facilitate the word processing in dyslexic populations (see Bachmann & Mengheri, 2018; Marinus et al., 2016; Perea et al, 2012; Zorzi et al., 2012; Benmarrakchi & El Kafi, 2021). Generally, these studies showed that reading performances for individuals with reading impairments decline when letters (and words) are presented closely together or when the font has a difficult design. Thus, setting inter-letter spacing and using a simple design would improve reading performance in individuals with dyslexia. Note, however, that the empirical evidence is not particularly conclusive (see Slattery et al., 2016, for a cautionary note). In a recent study on eye movements during reading, Łuniewska and colleagues (2022) found no significant impact of inter-letter spacing on reading speed or comprehension in readers with dyslexia, a result consistent with Hakvoort et al.'s (2017) earlier findings. However, it is possible that increased inter-letter spacing only benefits a subset of individuals with dyslexia who are particularly susceptible to visual crowding, as suggested by Joo et al. (2017). More multi-laboratory research is needed to settle the role of crowding and inter-letter (or inter-word) spacing during reading.

Interestingly, research on visual word recognition also provided some ideas to enhance learning to read. For instance, Perea and Wang (2017) proposed an innovative method to learn Chinese that can be extended to other writing systems that do not employ interword spaces: colors. The logic was that, at the early stages of learning to read in unspaced writing systems, color information provides a useful visual cue to help to segment the words (e.g., 大象打算在森林开一家商店 [The elephant plans to open a store in the forest]), facilitating the reading process. Perea and Wang (2017) found that alternating colors across words in Chinese facilitated the process of word identification for young readers—they also found a parallel advantage for adult readers when the text contained unfamiliar words. Subsequent research has generalized this finding to adult learners of Chinese as L2 (see Zhou et al., 2020). In a similar vein, Pan et al. (2021) showed that, in Chinese children, the benefit of the sentences with alternating colors decreased as a function of Grade (i.e., a strong benefit in Grades 2 and 3, but not on Grades 4 and 5). Furthermore, alternating the colors across words in Chinese may help eye guidance during reading (i.e., location closer to the optimal viewing position; see Zhou et al., 2018). Thus, using colors to separate words could be helpful for children or adult individuals who are learning to read and write in unspaced writing system (e.g., Chinese, Japanese, Thai, Javanese, among others).

Methodological advances on the research of visual-word recognition

Besides the theoretical and educational implications outlined earlier, the field of visual word recognition has a long tradition of leading to significant advancements in terms of methodological innovation. One such development in the past was the use of F2 Analyses of Variance and the minF' statistics in generalizing the effects of visual-word recognition across different items (i.e., avoiding the so-called "item-as-a-fixed-effect" fallacy; see Raaijmakers et al., 1999, for review). This emphasis on generalization across items is crucial for understanding the reliability of an effect: an effect that is robust when analyzed by subjects but not by items is likely driven by a small subset of items (see Mitterer, 2022, for criticism of recent research in social psychology). This approach minimizes the fact that the findings could have been due to an unfortunate stimulus selection. Thus, it is not surprising that the reliance on generalizing effects across both subjects and items has enabled research in this area to navigate the replication crisis in psychology with greater success than other areas. Indeed, most of the landmark findings in the literature have usually been replicated without difficulties (e.g., see Häsennacker et al., 2021, for discussion and suggestions).

In the last decade, the area of visual-word recognition shifted away from traditional analyses of variance and has adopted linear mixed-effects models (see Baayen & Milin, 2010, for early research on this issue). These models enable the modeling of individual observations, rather than aggregate data, by both subjects and items as random factors. This approach requires more effort from researchers as it necessitates explicit specification of the models in terms of random factors (Barr et al., 2013). Thus, all these steps require a justification of the model building process—both confirmatory and exploratory analyses. Additionally, researchers need to specify other characteristics, such as the underlying distribution of the data. Given that the main dependent variable in experiments on word recognition is response time, this poses the added challenge of specifying the theoretical distribution for the fits. This may require a non-linear transformation, such as an inverse Gaussian distribution via a -1000/RT transformation, or it may not, such as using the exGaussian distribution (i.e., the convolution of the normal and the exponential distributions) or the lognormal distributions. Though the findings are often similar regardless of the transformation (Perea, Gomez, & Baciero, 2023), it is always desirable to minimize the authors' degrees of freedom by pre-registering the analyses (e.g., in the Open Science Foundation) and making all scripts and stimulus materials available. Furthermore, reporting the results of linear mixed-effects models in a transparent and systematic manner is essential. To that end, it is important to have clear guidelines for doing so (see Meteyard & Davies, 2020, for an excellent example). In addition to transparent reporting, sharing the data and scripts in a public repository (e.g., in the open science foundation website) is also highly desirable.

In response to interpretive issues associated with frequentist analyses, particularly in regards to the limitations of p-values in null hypothesis testing, the field of visual-word recognition has seen a rapid adoption of Bayesian methods (Wagenmakers et al., 2010). For example, Gomez and Perea (2014) reported the findings of a word recognition experiment using solely Bayes Factors, which are indexes of the likelihood of the data given a simpler or more complex model, without utilizing p-values. This approach is becoming increasingly prevalent in the field. Furthermore, for statistical analysis using mixed-effects models, it is now becoming standard practice to use Bayesian models (e.g., via the *brms* package, Bürkner, 2018), using 95% credible intervals of the posterior distributions of the parameters as a criterion for evidence (e.g., see Dänbock et al., 2023; Fernández-López et al., 2023)—note that these distributions are less affected by the choice of priors than Bayes Factors. Additionally, these Bayesian models have the added advantage of avoiding the convergence problems often encountered with frequentist packages for linear-mixed effects.

Furthermore, researchers in the field are currently utilizing deep learning techniques to simulate the neural encoding of words, providing a fresh perspective on the field (Hannagan et al., 2021; Yin et al., 2022). Lastly, the use of multilingual approaches to studying visual-word recognition and reading using large corpora (e.g., the Multilingual Eye-movement Corpus [MECO], Siegelman et al., 2022) offers exciting opportunities to model a wide range of phenomena related to both monolingual and bilingual reading.

Conclusions

The field of visual word recognition is a lively, multi-faceted area of research with many edges—of which we have only sketched a minimal proportion. Furthermore, it lies on the bridge of many neighboring areas beyond the realm of the "word nerds". As a result, the field benefits from the synergies of researchers from different fields (educational psychologists, mathematical psychologists, cognitive scientists, speech therapists, etc.). Similarly, the area has contributed to the improvement of educational techniques together with methodological innovations—one of them is the widespread use of pre-registered studies and multi-lab approaches to word recognition (e.g., see Buchanan et al., 2022).

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Conflict of interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Adelman, J. S. (2011). Letters in time and retinotopic space. *Psychological Review, 118*, 570–582. https://doi.org/10.1037/a0024 811

Adelman, J. S., Brown, G. D., & Quesada, J. F. (2006). Contextual diversity, not word frequency, determines word-naming and lexical decision times. *Psychological Science, 17*, 814–823. https://doi.org/10.1111/j.1467-9280.2006.01787.x

Adelman, J. S., Gubian, M., & Davis, C. J. (2018). *easyNet: A computational modeling software package for cognitive science, bridging the gap between novices and experts* [Computer software]. http://adelmanlab.org/easyNet/

Adelman, J. S., Johnson, R. L., McCormick, S. F., McKague, M., Kinoshita, S., Bowers, J. S., … Davis, C. J. (2014). A behavioral database for masked form priming. *Behavior Research Methods, 46*, 1052–1067. https://doi.org/10.3758/s13428-013-0442-y

Aguasvivas, J., Carreiras, M., Brysbaert, M., Mandera, P., Keuleers, E., & Duñabeitia, J. A. (2020). How do Spanish speakers read words? Insights from a crowdsourced lexical decision megastudy. *Behavior Research Methods, 52*, 1867–1882. https://doi.org/10.3758/s13428-020-01357-9

Álvarez, C. J., Carreiras, M., & Perea, M. (2004). Are syllables phonological units in visual word recognition? *Language and Cognitive Processes, 19*, 427–452. https://doi.org/10.1080/01690960344000242

Andrews, S. (1996). Lexical retrieval and selection processes: Effects of transposed-letter confusability. *Journal of Memory and Language, 35*, 775–800. https://doi.org/10.1006/jmla.1996.0040

Angele, B., Baciero, A., Gómez, P., & Perea, M. (2023). Does online masked priming pass the test? The effects of prime exposure duration on masked identity priming. *Behavior Research Methods, 55*, 151–167. https://doi.org/10.3758/s13428-021-01742-y

Baayen, R. H., & Milin, P. (2010). Analyzing reaction times. *International Journal of Psychological Research*, *3*(2), 12–28. https://doi.org/10.21500/20112084.807

Bachmann, C., & Mengheri, L. (2018). Dyslexia and fonts: Is a specific font useful? *Brain Sciences, 8*(5), 89. https://doi.org/10.3390/brainsci8050089

Baciero, A., Gómez, P., Duñabeitia, J. A., & Perea, M. (2022). Raeding with the fingres. Towards a universal model of letter position coding. *Psychonomic Bulletin & Review, 29*, 2275–2283. https://doi.org/10.3758/s13423-022-02078-0

Baciero, A., Gómez, P., Duñabeitia, J. A., & Perea, M. (2023). Letter-similarity effects in braille word recognition. *Quarterly Journal of Experimental Psychology*. https://doi.org/10.1177/17470218221142145

Baciero, A., Labusch, M., Rocabado, F., Perea, M., & Marcet, A. (2021). ¿Por qué es tan fácil falsificar un logo? *Ciencia Cognitiva*, *15*(2), 24–27.

Balota, D. A., Yap, M. J., Cortese, M. J., Hutchison, K. A., Kessler, B., Loftis, B., ... Treiman, R. (2007). The English lexicon project. *Behavior Research Methods, 39*, 445–459. https://doi.org/10.3758/bf03193014

Balota, D. A., Yap, M. J., Hutchison, K. A., & Cortese, M. J. (2012). Megastudies: What do millions (or so) of trials tell us about lexical processing? In J. S. Adelman (Ed.), *Visual word recognition: Models and methods, orthography and phonology* (pp. 90–115). Psychology Press.

Balota, D., Yap, M. J., & Cortese, M. J. (2006). Visual word recognition: The journey from features to meaning (a travel update). In M. Traxler & M. A. Gernsbacher (Eds.), *Handbook of psycholinguistics*, 2nd ed. (pp. 285–375). Academic Press.

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language, 68*, 255–278. https://doi.org/10.1016/j.jml.2012.11.001

Benmarrakchi, F., & El Kafi, J. (2021). Investigating Reading Experience of Dyslexic Children Through Dyslexia-Friendly Online Learning Environment. *International Journal of Information and Communication Technology Education (IJICTE), 17*, 105–119. https://doi.org/10.4018/IJICTE.2021010107

Bowers, J. S., Malhotra, G., Dujmović, M., Montero, M. L., Tsvetkov, C., Biscione, V., … Blything, R. (2022). Deep problems with Neural Network Models of human vision. *Brain and Behavioral Sciences*. https://doi.org/10.1017/S0140525X22002813

Brysbaert, M., Stevens, M., Mandera, P., & Keuleers E. (2016). The impact of word prevalence on lexical decision times: Evidence from the Dutch Lexicon Project 2. *Journal of Experimental Psychology: Human Perception and Performance, 42*, 441–458. https://doi.org/10.1037/xhp0000159

Brysbaert, M., Stevens, M., Mandera, P., & Keuleers, E. (2016). The impact of word prevalence on lexical decision times: Evidence from the Dutch Lexicon Project 2. *Journal of Experimental Psychology: Human Perception and Performance, 42*, 441–458. https://doi.org/10.1037/xhp0000159

Buchanan, E.M., Cuccolo, K., Lewis, S., Heyman, T., Xiaolin, M.M., Iyer, A., … Zugarramurdi, C. (2022, November). *Is priming consistent across languages? Preliminary findings from the SPAML: Semantic Priming Across Many Languages*. Spoken presentation at the Annual Meeting of the Psychonomic Society, Boston, MA.

Bürkner, P. C. (2020). Analysing standard progressive matrices (SPM-LS) with Bayesian item response models. *Journal of Intelligence, 8*, 5. https://doi.org/10.3390/jintelligence8010005

Caldwell-Harris, C. L. (2021). Frequency effects in reading are powerful—but is contextual diversity the more important variable? *Language and Linguistic Compass*, *15*, e12444. https://doi.org/10.1111/lnc3.12444

Carreiras, M., Álvarez, C. J., & de Vega, M. (1993). Syllable frequency and visual word recognition in Spanish. *Journal of Memory and Language, 32*, 766–780. https://doi.org/10.1006/jmla.1993.1038

Carreiras, M., Armstrong, B. C., Perea, M., & Frost, R. (2014). The what, when, where, and how of visual word recognition. *Trends in Cognitive Sciences, 18*, 90–98. https://doi.org/10.1016/j.tics.2013.11.005

Carreiras, M., Perea, M., Gil-López, C., Abu Mallouh, R., & Salillas, E. (2013). Neural correlates of visual vs. abstract letter processing in Roman and Arabic scripts. *Journal of Cognitive Neuroscience, 25*, 1975–1985. https://doi.org/10.1162/jocn_a_00438

Casaponsa, A., & Duñabeitia, J. A. (2016). Lexical organization of language-ambiguous and language-specific words in bilinguals*.* *Quarterly Journal of Experimental Psychology, 69*, 589–604. https://doi.org/10.1080/17470218.2015.1064977

Castles, A., Davis, C., Cavalot, P., & Forster, K. (2007). Tracking the acquisition of orthographic skills in developing readers: Masked priming effects. *Journal of Experimental Child Psychology, 97*, 165–182. https://doi.org/10.1016/j.jecp.2007.01.006

Coltheart, M., Rastle, K., Perry, C., Langdon, R., & Ziegler, J. (2001). DRC: A dual route cascaded model of visual word recognition and reading aloud. *Psychological Review, 108*, 204–256. https://doi.org/10.1037/0033-295X.108.1.204

Commissaire, E. (2022). Do both WRAP and TRAP inhibit the recognition of the French word DRAP? Impact of orthographic markedness on cross-language orthographic priming. *Quarterly Journal of Experimental Psychology, 75*, 1094–1113. https://doi.org/10.1177/17470218211048770

Conrad, M., Tamm, S., Carreiras, M., & Jacobs, A. M. (2010). Simulating syllable frequency effects within an interactive activation framework. *European Journal of Cognitive Psychology, 22*, 861–893. https://doi.org/10.1080/09541440903356777

Danböck, S. K., Franke, L. K., Miedl, S. F., Liedlgruber, M., Bürkner, P. C., & Wilhelm, F. H. (2023). Experimental induction of peritraumatic dissociation: The role of negative affect and pain and their psychophysiological and neural correlates. *Behaviour Research and Therapy, 164*, 104289. https://doi.org/10.1016/j.brat.2023.104289

Davis, C. J. (2010). The spatial coding model of visual word identification. *Psychological Review, 117*, 713–758. http://dx.doi.org/10.1037/a0019738

Dehaene, S., & Cohen, L. (2007). Cultural recycling of cortical maps. *Neuron*, *56*, 384–398. http://dx.doi.org/10.1016/j.neuron.2007.10.004

Dehaene, S., Cohen, L., Sigman, M., & Vinckier, F. (2005). The neural code for written words: A proposal. *Trends in Cognitive Sciences, 9*, 335–341. https://doi.org/10.1016/j.tics.2005.05.004

Dijkstra, T., van Heuven, W. J. B., & Grainger, J. (1998). Simulating cross-language competition with the bilingual interactive activation model. *Psychologica Belgica, 38*(3-4), 177–196. https://doi.org/10.5334/pb.933

Fernández-López, M., Gómez, P., & Perea, M. (2021a). Which factors modulate letter position coding in pre-literate children? *Frontiers in Psychology, 12*, 708274. https://doi.org/10.3389/fpsyg.2021.708274

Fernández-López, M., Gomez, P., & Perea, M. (2023). Letter rotations: Through the magnifying glass and what evidence found there. *Language, Cognition, and Neuroscience, 38*, 127-138. https://doi.org/10.1080/23273798.2022.2093390

Fernández-López, M., Marcet, A., & Perea, M. (2021b). Does orthographic processing emerge rapidly after learning a new script? *British Journal of Psychology, 112*, 52–91. https://doi.org/10.1111/BJOP.12469

Fernández-López, M., Mirault, J., Grainger, J., & Perea, M. (2021c). How resilient is reading to letter rotations? A parafoveal preview investigation. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 47*, 2029–2042. https://doi.org/10.1037/xlm0000999

Ferrand, L., New, B., Brysbaert, M., Keuleers, E., Bonin, P., Méot, A., … Pallier, C. (2010). The French lexicon project: Lexical decision data for 38,840 French words and 38,840 pseudowords. *Behavior Research Methods, 42*, 488–496. https://doi.org/10.3758/BRM.42.2.488

Frost, R. (1998). Toward a strong phonological theory of visual word recognition: True issues and false trails. *Psychological Bulletin, 123*, 71–99. https://doi.org/10.1037/0033-2909.123.1.71

Gabrieli, J. D. (2009). Dyslexia: A new synergy between education and cognitive neuroscience. *Science*, *325*(5938), 280–283. https://doi.org/10.1126/science.1171999

Galliussi, J., Perondi, L., Chia, G., Gerbino, W., & Bernardis, P. (2020). Inter-letter spacing, inter-word spacing, and font with dyslexia-friendly features: testing text readability in people with and without dyslexia. *Annals of Dyslexia*, *70*(1), 141–152. https://doi.org/10.1007/s11881-020-00194-x

García-Orza, J., & Perea, M. (2011). Position coding in two-digit Arabic numbers: Evidence from number decision and same-different tasks. *Experimental Psychology, 58*, 85–91. https://doi.org/10.1027/1618-3169/a000071

Gomez, P., & Perea, M. (2014). Decomposing encoding and decisional components in visual-word recognition: A diffusion model analysis. *Quarterly Journal of Experimental Psychology, 67*, 2455–2466. https://doi.org/10.1080/17470218.2014.937447

Gomez, P., & Perea, M. (2020). Masked identity priming reflects an encoding advantage in developing readers. *Journal of Experimental Child Psychology, 199*, 104911. https://doi.org/10.1016/j.jecp.2020.104911

Gómez, P., Marcet, A., & Perea, M. (2021). Are better young readers more likely to confuse their mother with their mohter? *Quarterly Journal of Experimental Psychology, 74*, 1542–1552. https://doi.org/10.1177/17470218211012960

Gomez, P., Ratcliff, R., & Perea, M. (2008). The overlap model: A model of letter position coding. *Psychological Review, 115*, 577–600. https://doi.org/10.1037/a0012667

Grainger, J. (2018). Orthographic processing: A "mid-level" vision of reading. *Quarterly Journal of Experimental Psychology, 71*, 335–359. https://doi.org/10.1080/17470218.2017.1314515

Grainger, J., & Holcomb, P. J. (2009). Watching the word go by: on the time-course of component processes in visual word recognition. *Language and Linguistic Compass, 3*, 128–156. https://doi.org/10.1111/j.1749-818X.2008.00121.x

Grainger, J., & Jacobs, A. M. (1996). Orthographic processing in visual word recognition: A multiple read-out model. *Psychological Review, 103*, 518–565. https://doi.org/10.1037/0033-295X.103.3.518

Grainger, J., & van Heuven, W. J. B. (2003). Modeling letter position coding in printed word perception. In P. Bonin (Ed.), *Mental lexicon: Some words to talk about words* (pp. 1–23). Nova Science Publishers.

Grainger, J., & Ziegler, J. C. (2011). A dual-route approach to orthographic processing. *Frontiers in Psychology, 2*, 54. https://doi. org/10. 3389/fpsyg. 2011.00054

Grainger, J., Granier, J. P., Farioli, F., Van Assche, E., & van Heuven, W. J. (2006). Letter position information and printed word perception: The relative-position priming constraint. *Journal of Experimental Psychology: Human Perception and Performance, 32*, 865–884. http://dx.doi.org/10.1037/0096-1523.32.4.865

Grainger, J., O'Regan, J. K., Jacobs, A. M., & Segui, J. (1989). On the role of competing word units in visual word recognition: The neighborhood frequency effect. *Perception & Psychophysics, 45*, 189–195. https://doi.org/10.3758/BF03210696

Guasch, M., Boada, J., Duñabeitia, J. A., & Ferré, P. (2022). Prevalence norms for 40,777 Catalan words: An online megastudy of vocabulary size. *Behavior Research Methods*. https://doi.org/10.3758/s13428-022-01959-5

Gutiérrez-Sigut, E., Marcet, A., & Perea, M. (2019). Tracking the time course of letter visual-similarity effects during word recognition: A masked priming ERP investigation. *Cognitive, Affective, and Behavioral Neuroscience, 19*, 966–984. http://dx.doi.org/10.3758/s13415-019-00696-1

Gutierrez-Sigut, E., Vergara-Martínez, M., & Perea, M. (2022). The impact of visual cues during visual word recognition in deaf readers: An ERP study. *Cognition, 218*, 104938. https://doi.org/10.1016/j.cognition.2021.104938

Hakvoort, B., van den Boer, M., Leenaars, T., Bos, P., & Tijms, J. (2017). Improvements in reading accuracy as a result of increased interletter spacing are not specific to children with dyslexia. *Journal of Experimental Child Psychology, 164*, 101–116. https://doi.org/10.1016/j.jecp.2017.07.010

Hannagan, T., Agrawal, A., Cohen, L., & Dehaene, S. (2021). Emergence of a compositional neural code for written words: Recycling of a convolutional neural network for reading. *Proceedings of the National Academy of Science USA, 118*, e2104779118. https://doi.org/10.1073/pnas.2104779118

Hasenäcker, J., Ktori, M., & Crepaldi, D. (2021). Morpheme position coding in reading development as explored with a letter search task. *Journal of Cognition, 4*(1), 16. https://doi.org/10.5334/joc.153

Hinojosa, J. A., Moreno, E. M., & Ferré, P. (2020). Affective neurolinguistics: towards a framework for reconciling language and emotion. *Language, Cognition and Neuroscience, 35*, 813–839. https://doi.org/10.1080/23273798.2019.1620957

Hutzler, F., Ziegler, J. C., Perry, C., Wimmer, H., & Zorzi, M. (2004). Do current connectionist learning models account for reading development in different languages? *Cognition, 91*, 273–296. https://doi.org/10.1016/j.cognition.2003.09.006

Izura, C., Pérez, M. A., Agallou, E., Wright, V. C., Marín, J., Stadthagen-González, H., & Ellis, A. W. (2011). Age/order of acquisition effects and the cumulative learning of foreign words: A word training study. *Journal of Memory and Language, 64*, 32-58. https://doi.org/10.1016/j.jml.2010.09.002

Jacobs, A. M., Rey, A., Ziegler, J. C., & Grainger, J. (1998). MROM-p: An interactive activation, multiple readout model of orthographic and phonological processes in visual word recognition. In J. Grainger & A. M. Jacobs (Eds.), *Localist connectionist approaches to human cognition* (pp. 147–188). Erlbaum.

Johnson, R. L., Perea, M., & Rayner, K. (2007). Transposed-letter effects in reading: Evidence from eye movements and parafoveal preview. *Journal of Experimental Psychology: Human Perception and Performance, 33*, 209–229. https://doi.org/10.1037/0096-1523.33.1.209

Jones, M. N., Johns, B. T., & Recchia, G. (2012). The role of semantic diversity in lexical organization. *Canadian Journal of Experimental Psychology, 66*, 115–124. https://doi.org/10.1037/a0026727

Joo, S. J., White, A. L., Strodtman, D. J., & Yeatman, J. D. (2018). Optimizing text for an individual's visual system: The contribution of visual crowding to reading difficulties. *Cortex, 103*, 291–301. https://doi.org/10.1016/j.cortex.2018.03.013

Juhasz, B. J. (2005). Age-of-acquisition effects in word and picture identification. *Psychological Bulletin, 131*, 684–712. https://doi.org/10.1037/0033-2909.131.5.684

Kohnen, S., Nickels, L., Castles, A., Friedmann, N., & McArthur, G. (2012). When 'slime' becomes 'smile': Developmental letter position dyslexia in English. *Neuropsychologia*, *50*, 3681–3692. https://doi.org/10.1016/j.neuropsychologia.2012.07.016

Labusch, M., Massol, S., Marcet, A., & Perea, M. (2023). Are goats chèvres, chévres, chēvres, and chevres? Unveiling the orthographic code of diacritical vowels. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 49,* 301–319. https://doi.org/10.1037/xlm0001212

Lázaro, M., García L., Illera V. (2021). Morpho-orthographic segmentation of opaque and transparent derived words: New evidence for Spanish. *Quarterly Journal of Experimental Psychology, 74*, 944–954. https://doi.org/10.1177/1747021820977038

Li, X., Huang, L., Yao, P., & Hyönä, J. (2022). Universal and specific reading mechanisms across different writing systems. *Nature Reviews Psychology, 1*(3), 133–144. https://doi.org/10.1038/s44159-022-00022-6

Łuniewska, M., Wójcik, M., & Jednoróg, K. (2022). The effect of inter-letter spacing on reading performance and eye movements in typically reading and dyslexic children. *Learning and Instruction, 80*, 101576. https://doi.org/10.1016/j.learninstruc.2021.101576

Mandera, P., Keuleers, E., & Brysbaert, M. (2020). Recognition times for 62 thousand English words: Data from the English Crowdsourcing Project. *Behavior Research Methods, 52*, 741–760. https://doi.org/10.3758/s13428-019-01272-8

Marcet, A., & Perea, M. (2017). Is nevtral NEUTRAL? Visual similarity effects in the early phases of written-word recognition. *Psychonomic Bulletin and Review, 24*, 1180–1185. http://dx.doi.org/10.3758/s13423-016-1180-9

Marcet, A., & Perea, M. (2018a). Can I order a burger at rnacdonalds.com? Visual similarity effects of multi-letter combinations at the early stages of word recognition. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 44*, 699–706. http://dx.doi.org/10.1037/xlm0000477

Marcet, A., & Perea, M. (2018b). Visual letter similarity effects during sentence reading: Evidence from the boundary technique. *Acta Psychologica, 190*, 142–149. http://dx.doi.org/10.1016/j.actpsy.2018.08.007

Marcet, A., & Perea, M. (2022). Does omitting the accent mark in a word affect sentence reading? Evidence from Spanish. *Quarterly Journal of Experimental Psychology, 75*, 148–155. http://dx.doi.org/10.1177/17470218211044694

Marcet, A., Fernández-López, M., Baciero, A., Sesé, A., & Perea, M. (2022). What are the letters e and é in a language with vowel reduction? The case of Catalan. *Applied Psycholinguistics, 43*, 193–210. http://dx.doi.org/10.1017/S0142716421000497

Marcet, A., Fernández-López, M., Labusch, M., & Perea, M. (2021). The omission of accent marks does not hinder word recognition: Evidence from Spanish. *Frontiers in Psychology*, *12*, 794923. https://doi.org/10.3389/fpsyg.2021.794923

Marcet, A., Perea, M., Baciero, A., & Gómez, P. (2019). Can letter position encoding be modified by visual perceptual elements? *Quarterly Journal of Experimental Psychology, 72*, 1344–1353. https://doi.org/10.1177/1747021818789876

Marinus, E., Mostard, M., Segers, E., Schubert, T. M., Madelaine, A., & Wheldall, K. (2016). A special font for people with dyslexia: Does it work and, if so, why? *Dyslexia*, *22*, 233–244. https://doi.org/10.1002/dys.1527

Massol, S., & Grainger, J. (2022). Effects of horizontal displacement and inter-character spacing on transposed-character effects in same-different matching. *PLoS ONE, 17*, e0265442. https://doi.org/10.1371/journal.pone.0265442

Massol, S., Duñabeitia, J. A., Carreiras, M., & Grainger, J. (2013). Evidence for letter-specific position coding mechanisms. *PLoS ONE, 8*, e68460. https://doi.org/10.1371/journal.pone.0068

McClelland, J. L., & Rumelhart, D. E. (1981). An interactive activation model of context effects in letter perception: Part 1. An account of basic findings. *Psychological Review, 88*, 375–407. https://doi.org/10.1037/0033-295X.88.5.375

McClelland, J. L., & Rumelhart, D. E. (1988). *Explorations in parallel distributed processing: A handbook of models, programs, and exercises*. MIT Press.

Meteyard, L., & Davies, R. A. (2020). Best practice guidance for linear mixed-effects models in psychological science. *Journal of Memory and Language, 112*, 104092. https://doi.org/10.1016/j.jml.2020.104092

Mittterer, H. (2022). A “names-as-fixed-effect fallacy” in studies of name-based racial discrimination. PNAS, 119 (38) e2209603119, https://doi.org/10.1073/pnas.2209603119

Morton, J. (1969). Interaction of information in word recognition. *Psychological Review, 76*, 165–178. https://doi.org/10.1037/h0027366

Norris, D., Kinoshita, S., & van Casteren, M. (2010). A stimulus sampling theory of letter identity and order. *Journal of Memory and Language, 62*, 254–271. https://doi.org/10.1016/j.jml.2009.11.002

Paap, K. R., Newsome, S. L., McDonald, J. E., & Schvaneveldt, R. W. (1982). An activation–Verification model for letter and word recognition: The word-superiority effect. *Psychological Review, 89*, 573–594. http://dx.doi.org/10.1037/0033-295x.89.5.573

Pagán, A., Blythe, H. I., & Liversedge, S. P. (2021). The influence of children's reading ability on initial letter position encoding during a reading-like task. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 47,* 1186–1203. https://doi.org/10.1037/xlm0000989

Pan, J., Liu, M., Li, H., & Yan, M. (2021). Chinese children benefit from alternating-color words in sentence reading. *Reading and Writing, 34*, 355–369. https://doi.org/10.1007/s11145-020-10067-9

Pathak, A., Velasco, C., & Calvert, G. A. (2019). Identifying counterfeit brand logos: On the importance of the first and last letters of a logotype. *European Journal of Marketing, 53*, 2109–2125. https://doi.org/10.1108/EJM-09-2017-0586

Perea M., Gómez, P., & Baciero, A. (2023). Do diacritics entail an early processing cost in the absence of abstract representations? Evidence from masked priming in English. *Language and Speech, 66,* 105–117. https://doi.org/10.1177/00238309221078321

Perea, M., & Lupker, S. J. (2003). Does jugde activate COURT? Transposed-letter similarity effects in masked associative priming. *Memory & Cognition, 31*, 829–841. https://doi.org/10.3758/BF03196438

Perea, M., & Lupker, S. J. (2004). Can CANISO activate CASINO? Transposed-letter similarity effects with non-adjacent letter positions. *Journal of Memory and Language, 51*, 231–246. https://doi.org/10.1016/j.jml.2004.05.005

Perea, M., & Panadero, V. (2014). Does viotin activate violin more than viocin? On the use of visual cues during visual-word recognition. *Experimental Psychology, 61*, 23–29. https://doi.org/10.1027/1618-3169/a000223

Perea, M., & Pollatsek, A. (1998). The effects of neighborhood frequency in reading and lexical decision. *Journal of Experimental Psychology: Human Perception and Performance, 24*, 767–777. https://doi.org/10.1037//0096-1523.24.3.767

Perea, M., & Wang, X. (2017). Do alternating-color words facilitate reading aloud text in Chinese? Evidence with developing and adult readers. *Memory and Cognition, 45*, 1160–1170. https://doi.org/10.3758/s13421-017-0717-0

Perea, M., Fernández-López, M., & Marcet, A. (2020). What is the letter é? *Scientific Studies of Reading*, *24*, 434–443. https://doi.org/10.1080/10888438.2019.1689570

Perea, M., Giner, L., Marcet, A., & Gomez, P. (2016). Does extra interletter spacing help text reading in skilled adult readers? *Spanish Journal of Psychology, 19*, e26, 1–7. https://doi.org/10.1017/sjp.2016.28

Perea, M., Labusch, M., & Marcet, A. (2022). How are words with diacritical vowels represented in the mental lexicon? Evidence from Spanish and German. *Language, Cognition, and Neuroscience, 37*, 457–468. https://doi.org/10.1080/23273798.2021.1985536

Perea, M., Marcet, A., & Vergara-Martínez, M. (2016). Phonological-lexical feedback during early abstract encoding: The case of deaf readers. *PLoS One, 11*(1), e0146265. https://doi.org/10.1371/journal.pone.0146265

Perea, M., Marcet, A., Baciero, A., & Gómez, P. (2023). Reading about a RELO-VUTION. *Psychological Research*. https://doi.org/10.1007/s00426-022-01720-9

Perea, M., Soares, A. P., & Comesaña, M. (2013). Contextual diversity is a main determinant of word-identification times in young readers. *Journal of Experimental Child Psychology, 116*, 37–44. https://doi.org/10.1016/j.jecp.2012.10.014

Perfetti, C. A. (2017). Lexical quality revisited. In E. Segers & P. van den Broek (Eds.), *Developmental perspectives in written language and literacy: In honor of Ludo Verhoeven* (pp. 51–68). John Benjamins.

Perry, C. (2023). Graphemes are used when reading: Evidence from Monte Carlo simulation using word norms from mega-studies. *Quarterly Journal of Experimental Psychology*, *76*, 419–428. https://doi.org/10.1177/17470218221086533

Plaut, D. (1997). Structure and function in the lexical system: Insights from distributed models of word reading and lexical decision. *Language and Cognitive Processes, 12*, 765–806. https://doi.org/10.1080/016909697386682

Plummer, P., Perea, M., & Rayner, K. (2014). The influence of contextual diversity on eye movements in reading. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 40*, 275–283. https://doi.org/10.1037/a0034058

Pollatsek, A., & Treiman. R. (2015) (Eds.). *The Oxford Handbook on Reading*. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199324576.001.0001

Pollatsek, A., Lesch, M., Morris, R. K., & Rayner, K. (1992). Phonological codes are used in integrating information across saccades in word identification and reading. *Journal of Experimental Psychology: Human Perception and Performance, 18*, 148–162. https://doi.org/10.1037/0096-1523.18.1.148

Raaijmakers, J. G. W., Schrijnemakers, J. M. C., & Gremmen, F. (1999). How to deal with the language-as-fixed-effect-fallacy: Common misconceptions and alternative solutions. *Journal of Memory and Language, 41*, 416–426. https://doi.org/10.1006/jmla.1999.2650

Ratcliff, R., & Hendrickson, A. T. (2021). Do data from mechanical Turk subjects replicate accuracy, response time, and diffusion modeling results*? Behavior Research Methods, 53*, 2302–2325. https://doi. org/10. 3758/s13428-021-01573-x

Ratcliff, R., Gomez, P., & McKoon, G. (2004). A diffusion model account of the lexical decision task. *Psychological Review, 111*, 159–182. https://doi.org/10.1037/0033-295X.111.1.159

Rayner, K., & Duffy, S. A. (1986). Lexical complexity and fixation times in reading: Effects of word frequency, verb complexity, and lexical ambiguity. *Memory & Cognition, 14*, 191–201. https://doi.org/10.3758/BF03197692

Rayner, K., Reichle, E. D., Stroud, M. J., Williams, C. C., & Pollatsek, A. (2006). The effect of word frequency, word predictability, and font difficulty on the eye movements of young and older readers. *Psychology and Aging, 21*(3), 448–465. https://doi.org/10.1037/0882-7974.21.3.448

Reichle, E. (2021). *Computational Models of Reading: A Handbook*. Oxford University Press. https://doi.org/10.1093/oso/9780195370669.001.0001

Rodd, J. M., Cai, Z. G., Betts, H. N., Hanby, B., Hutchinson, C., & Adler, A. (2016). The impact of recent and long-term experience on access to word meanings: Evidence from large-scale internet-based experiments. *Journal of Memory and Language, 87*, 16–37. https://doi.org/10.1016/j.jml.2015.10.006

Rumelhart, D. E. (1977). Understanding and summarizing brief stories. In D. Laberge & S. J. Samuels (Eds.), *Basic processes in reading: Perception and comprehension* (pp. 265–303). Erlbaum.

Rumelhart, D. E., & McClelland, J. L. (1982). An interactive activation model of context effects in letter perception: Part 2. The contextual enhancement effect and some tests and extensions of the model. *Psychological Review, 89*, 60–94. https://doi.org/10.1037/0033-295X.89.1.60

Rumelhart, D. E., & Siple, P. (1974). Process of recognizing tachistoscopically presented words. *Psychological Review, 81*, 99–118. https://doi. org/10. 1037/h0036117

Schoonbaert, S., & Grainger, J. (2004). Letter position coding in printed word perception: Effects of repeated and transposed letters. *Language and Cognitive Processes, 19*, 333–367. https://doi.org/10.1080/01690960344000198

Schotter, E. R., Reichle, E. D., & Rayner, K. (2014). Rethinking parafoveal processing in reading: Serial-attention models can explain semantic preview benefit and N+2 preview effects. *Visual Cognition, 22*, 309–333. https://doi.org/10.1080/13506285.2013.873508

Sellés, P., Martínez, T., Vidal-Abarca, E., and Gilabert, R. (2008). *BIL 3–6. Batería de Inicio a la Lectura* [Battery to Assess the Abilities Related with Early Reading Acquisition]. Instituto de Ciencias de la Educación.

Seidenberg, M. S., & McClelland, J. L. (1989). A distributed, developmental model of word recognition and naming. *Psychological Review, 96*, 523–568. https://doi.org/10.1037/0033-295X.96.4.523

Selfridge, O. G. (1959). Pandemonium: A paradigm for learning. In D. V. Blake and A. M. Uttley (Eds.), *Proceedings of the Symposium on the mechanisation of thought processes* (pp. 511–529). H.M. Stationary Office

Siegelman, N., Schroeder, S., Acartürk, C., Ahn, H. D., Alexeeva, S., Amenta, S., ... & Kuperman, V. (2022). Expanding horizons of cross-linguistic research on reading: The Multilingual Eye-movement Corpus (MECO). *Behavior Research Methods*, *54*, 2843–2863. https://doi.org/10.3758/s13428-021-01772-6

Slattery, T. J., Yates, M., & Angele, B. (2016). Interword and interletter spacing effects during reading revisited: Interactions with word and font characteristics. *Journal of Experimental Psychology: Applied*, *22*, 406-422. https://doi.org/10.1037/xap0000104

Snell, J., van Leipsig, S., Grainger, J., & Meeter, M. (2018). OB1-reader: A model of word recognition and eye movements in text reading. *Psychological Review, 125*, 969–984. https://doi.org/10.1037/rev0000119

Snowling, M. J., Hulme, C., & Nation, K. (2022) (Eds.). *The Science of Reading: A Handbook, 2nd Edition*. Wiley. https://doi.org/10.1002/9781119705116

Song, Z., Liang, X., Wang, Y., & Yan, G. (2021). Effect of alternating-color words on oral reading in grades 2–5 Chinese children: Evidence from eye movements. *Reading and Writing, 34*, 2627–2643. https://doi.org/10.1007/s11145-021-10164-3

Trifonova, I. V., & Adelman, J. S. (2019). A delay in processing for repeated letters: Evidence from megastudies. *Cognition, 189*, 227–241. https://doi.org/10.1016/j.cognition.2019.04.005

van Heuven, W. J., & Dijkstra, T. (2010). Language comprehension in the bilingual brain: fMRI and ERP support psycholinguistic models. *Brain Research Reviews, 64*, 104–122. https://doi.org/10.1016/j.brainresrev.2010.03.002

Vergara-Martínez, M., Comesaña, M., & Perea, M. (2017). The ERP signature of the contextual diversity effect in visual word recognition. *Cognitive, Affective, and Behavioral Neuroscience, 17*, 461–474. https://doi.org/10.3758/s13415-016-0491-7

Vergara-Martínez, M., Gomez, P., Jiménez, M., & Perea, M. (2015). Lexical enhancement during prime-target integration: ERP evidence from matched-case identity priming. *Cognitive, Affective, & Behavioral Neuroscience, 15*, 492–504. https://doi.org/10.3758/s13415-014-0330-7

Wagenmakers, E.-J., Lodewyckx, T., Kuriyal, H., and Grasman, R. (2010). Bayesian hypothesis testing for psychologists: A tutorial on the Savage-Dickey method. *Cognitive Psychology, 60*, 158–189. https://doi.org/10.1016/j.cogpsych.2009.12.001

Williams, C. C., Perea, M., Pollatsek, A., & Rayner, K. (2006). Previewing the neighborhood: The role of orthographic neighbors as parafoveal previews in reading. *Journal of Experimental Psychology: Human Perception and Performance, 32,* 1072–1082. https://doi.org/10.1037/0096-1523.32.4.1072

Yin, D., Bowers, J., & Biscione, V. (2023). Convolutional Neural Networks trained to identify words provide a good account of visual form priming effects. *Computational Brain & Behavior*. https://doi.org/10.21203/rs.3.rs-2289281/v1

Ziegler, J.C., Perry, C., & Coltheart, M. (2000). The DRC model of visual word recognition and reading aloud: An extension to German. *European Journal of Cognitive Psychology, 12*, 413–430. https://doi.org/10.1080/09541440050114570

Zhou, W., Wang, A., Shu, H., Kliegl, R., & Yan, M. (2018). Word segmentation by alternating colors facilitates eye guidance in Chinese reading. *Memory & Cognition, 46*, 729–740. https://doi.org/10.3758/s13421-018-0797-5

Zhou, W., Ye, W., & Yan, M. (2020). Alternating-color words facilitate reading and eye movements among second-language learners of Chinese. *Applied Psycholinguistics, 41*, 685–699. https://doi.org/10.1017/S0142716420000211

Zorzi M., Houghton G., & Butterworth B. (1998). Two routes or one in reading aloud? A connectionist dual-process model. *Journal of Experimental Psychology: Human Perception & Performance, 24*, 1131–1161. https://doi.org/10.1037/0096-1523.24.4.1131