Theoretical 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 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, 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. 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, 2022; 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 edited book by Pollatsek & Treiman, 2015). Instead, the present paper aims to offer a brief—and necessarily subjective—overview of the current state of the models of visual-word recognition, including some of their existing challenges. We then focus on the educational implications of studies on visual word recognition, often underexplored, and on the importance of this field when pioneering novel methodological approaches.

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

A brief historical analyses of models of visual-word recognition

The first mainstream 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 and the one that reaches the threshold level of activation represents the identified word. The following groundbreaking step was the implementation of the first computational models of visual-word recognition (localist models): the interactive-activation model (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982) and the activation-verification model (Paap et al., 1982), both having three main layers of detectors (letter features, letters, and words).

The interactive-activation model was subsequently at the core of more sophisticated models of visual-word recognition, including the multiple-read out model (Grainger & Jacobs, 1996), the lexical module of the dual-route cascaded [DRC] model (Coltheart et al., 2001), and the Bilingual Interactive Activation model (Dijkstra et al., 1998). In the 1980s, parallel distributed processing—also called connectionist—models of visual-word recognition (see McClelland & Rumelhart, 1988) were proposed as an alternative to the above-cited 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 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 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 coding scheme of the interactive-activation model, 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 these effects 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 ideas behind the overlap model (Gomez et al., 2008), the spatial coding model (Davis, 2010), and the Bayesian reader model (Norris et al., 2010)—note that 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 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 computational models of visual-word recognition have proposed hybrid mechanisms, including 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 computational models implemented easy-to-use and flexible computer programs. The best instance is the Spatial Coding model (Davis, 2010).[2] Furthermore, it is worth noting that there is computer software for modeling visual-word recognition:

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

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 models still have some limitations. 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 current 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 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 unexpected 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 logo) 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 (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 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).

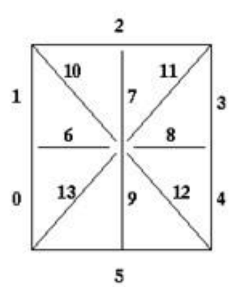

Figure 2. Letter matrix in the Rumelhart and Sipple (1974) font.

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. (2022) 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 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).

While a review of these important topics would go beyond the scope of the present 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. 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 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 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 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. (2021c) found that scores on a basic test of perception and memory predicted letter position encoding skills. These findings suggest that it is possible to identify very early (i.e., before literacy), some potential reading deficit via the assessment of the visual analyses of the input—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).

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. Specifically, they showed that alternating colors across words in unspaced scripts facilitated the process of word identification for young readers—and also for difficult words in skilled readers. Thus, at the early stages of learning to read, color information provides a visual cue to help to segment the words, facilitating the reading process (see Pan et al., 2021, for similar evidence during sentence reading in children).

Methodological advances on the research of visual-word recognition

Besides the theoretical and educational implications outlined earlier, the field of visual word recognition has produced significant advancements in terms of methodological innovation. One such development has been the use of F2 Analyses of Variance and the minF' statistics in generalizing the effects of visual-word recognition across different items (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. 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 recent years, the area of visual-word recognition has 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). 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.

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). Additionally, these 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.

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