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What, Where, When and How of Visual Word Recognition: A Bibliometrics Review

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Abstract

The neural/mental operations involved in the process of visual word recognition (VWR) are fundamental for the efficient comprehension of written/printed words during reading. The present study used CiteSpace, a visual analysis software, to identify the intellectual landscape where VWR has been reviewed in the past decade. Thus, synthesized co-citation networks were analyzed to explore and discuss the main questions raised in the VWR literature: the research fronts and the emerging trends of research on this topic. Our results showed that the main questions addressed in VWR studies during the last decade have been focused on four main aspects related to "what," "where," "when," and "how" of VWR; to be specific, the different types of representations assessed during VWR ("what"), the locations and the timing of the brain activity involved in VWR ("where" and "when"), and the interactivity among different representations during processing ("how"). Among the revised studies, letter position coding was found to be the main topic of interest, possibly reflecting the critical role of this process. Furthermore, the evidence found in these studies consistently supported that VWR implies access to phonological, semantic, and

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morphological representations, which interact and modulate the processing of written words, particularly during early stages. Altogether, our findings showed the evolution in VWR literature regarding the different cognitive and neural operations involved in this process, highlighting the growing interest over the last decade toward the top-down way that mental representations interact.

Keywords
Visual word recognition, CiteSpace, top-down processing, bibliometrics

1 Introduction

How do we recognize a written word? What are the processes that we need to access the meaning when we see a word? When we see a word, how do we access to its representation in the mental lexicon and how is it retrieved? When our eyes fixate on a written word, this visual window triggers the subsequent processing of orthographic, phonological, and semantic information (Grainger, 2008). This apparently basic process, generally referred to as visual word recognition (VWR), has been investigated from a range of perspectives (e.g., behavioral, neuropsychological; Wheat et al., 2010; Yap et al., 2012; and clinical, Bosse et al., 2007; Ramus et al., 2013; Vidyasagar & Pammer, 2010), methods (e.g., computational models, Coltheart et al., 2001; Perry et al., 2007; Perry et al., 2010; functional and structural neuroimaging, Flinker et al., 2015; Indefrey, 2011; Pickering & Gambi, 2018; Price & Devlin, 2011), and paradigms (e.g., priming, Rastle et al., 2000; Rastle & Brysbaert, 2006; lexical decision, Hauk et al., 2006; semantic categorization, Forster, 2004; or word naming, Balota et al., 2004; Cortese & Khanna, 2007; Cortese & Schock, 2013; Maloney et al., 2009). Generally, the focus of previous research in the broad field of cognitive psycholinguistics has been on the nature of printed (or written) word representations ("what") and the mechanisms by which they are processed ("how"). Moreover, the fast development and growing use of electromagnetic and functional neuroimaging techniques, over the last 20 years, have contributed to solving questions related to the "when" and "where" of VWR (Carreiras et al., 2014; see also Dehaene et al., 2015; Lerma et al., 2018; Martin et al., 2015). In this sense, research on the neural basis of VWR has shed light upon unique theoretical stances, providing precise explanations regarding the location or timing of neural processes. "What" and "how" questions are largely interdependent with the issues of "where" and "when" internal representations take place during VWR (Carreiras et al., 2014). However, to the best of our knowledge, this is the first bibliometric-based study on VWR that investigates different aspects of this process across a wide range of dimensions.

In recent years, bibliometric techniques have been applied to quantitatively evaluate research trends and tacit scientific knowledge in the literature by adopting mathematical, statistical, and other measurement methods (Yu et al., 2017, 2018). Compared with conventional expert-compiled reviews, which are typically based on expert-made interventions and prior knowledge of the topic, a bibliometric approach can help analysts visualize and break down co-citation networks on the basis of the algorithm of co-citation matrix. Therefore, this approach enables the identification of a much broader and more diverse range of relevant topics, providing in-depth reviews and insights about the field of study (Chen et al., 2014c; Zhu & Hua, 2017).

CiteSpace is a software for citation visualization analysis used to detect the knowledge foundation, emerging trends, and innovation modes of a field from a macroscopic perspective. It has been extensively used in a wide range of fields, including big data research (Xu & Yu, 2019), journal analysis (Li et al., 2019), finance (Li et al., 2020), medicine (Wu et al., 2020), and the environment (Sun et al., 2020). In particular, this software allows the visualization of networks of co-citation references based on bibliographic records retrieved from core collections of publications (Chen, 2012). CiteSpace is also designed to facilitate the analytic process of detecting emerging trends in the scientific literature and identifying future research directions (Chen, 2006; Chen et al., 2014b).

In the present study, we applied CiteSpace to delineate the structure and dynamics of the research frontier in VWR. In this way, synthesized networks of co-citation references, based on bibliographic records retrieved from the Web of Science, were generated and progressively analyzed. In particular, this bibliometric-based work conducts a quantitative analysis on the VWR research over the past decade, disentangling the "what," "where," "when," and "how" questions which have been the focus of research in the literature, including:

- What are the types of representations highlighted during the last decade?
- Where and when are these representations activated?
- How are they segmented, phonologically converted, assembled, and redirected from the sublexical to the lexical level for word identification?

In addition to examining the evolution of the literature on VWR through a multidimensional perspective, this study is intended to be a guide for nonspecialized researchers in the use of bibliometric methods in general, and of CiteSpace in particular, presenting a comprehensive description of the method and related key terms. In short, this study brings the use of bibliometrics to general, nonspecialized audiences in psycholinguistics, showing the potential benefits of this approach for exhaustive reviews in broad research fields such as VWR.

2 Methods

2.1 Data source and collection

In this study, the Web of Science Core Collection was chosen as the data source to build the dataset by collecting 2734 records from 1986 to 2018, based on a topic search of the term "visual word recognition" in titles, abstracts, or keywords. After filtering out less representative document types and non-English-language articles, the dataset was reduced to 2311 records. Terms for topic searches were carefully chosen. Notably, if we included records by using more reduced cue words, such as "word recognition," instead of the term "visual word recognition," the number of records could be five times bigger. Theoretically, the term "visual word recognition" tends to reveal the process concerned with the recognition of a written word (Grainger, 2008). In contrast, word recognition is more broadly related to how printed and spoken word recognition operates, which means that it is not only involved in recognizing visual words, but also concerned the process of accessing sound, reading, and learning how to spell (Gerrig, 1986; Johnson-Laird, 1975; see also Liberman et al., 1967). Even though the processing of spoken language is broadly consistent with that of written language, the demarcation between these two operations is that the speech signal is processed sequentially, phoneme by phoneme, whereas a printed word is accessible at once (Trevor, 2014). Given that this study specifically focuses on the recognition of a word when we access the representation from its visual features, choosing the term "visual word recognition" would be more appropriate for collecting the dataset.

Figure 1 shows the annual publication counts of all bibliographic records resulting from the search of the term "visual word recognition" and covering a time span from 1994 to 2018, with a remarkable enhancement since 2009. Therefore, our dataset was built by selecting publications

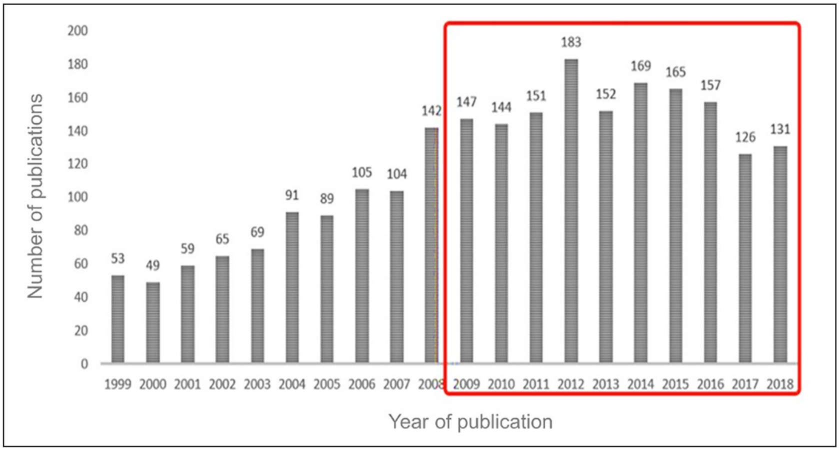

Figure 1. Annual publication counts from 1994 to 2018 in the Web of Science Core Collection based on the search topic VWR. Period framed in red corresponds to years from which bibliographic records were extracted for the present bibliometric study.

published between 2009 and 2018 (a total of 1525 entrances), in order to reveal the knowledge foundation and emerging fields of VWR research within the last decade.

2.2 CiteSpace

CiteSpace (available at http://cluster.ischool.drexel.edu/~cchen/citespace/download/) is designed to synthesize and visualize the literature in the form of a co-citation network in which co-cited references are represented as nodes (see Figure 2, for the illustration of a node). The citation history of a node is identified based on its tree-rings with different colors ranging from cold colors such as purple to warm colors such as orange. In addition, the citation history of a node can be visualized by the thickness of its tree-rings, which means that the larger the tree-ring a node has, the more frequently it is cited. For instance, the node shown in Figure 2 represents a reference published in 2007, and each tree-ring of the node indicates the number of citations it received in the corresponding year (e.g., tree-ring colored in orange indicates the citation counts of the node in 2017). Moreover, nodes are grouped into clusters depending on the relativity and interconnectivity between references on a specific research topic (Chen, 2006). Thus, each cluster represented in the co-citation network depicts a specific research topic. In what follows, a series of parameters in relation to the analysis of a cluster are described (see Table 1 for a quick reference guide, listing all basic terms referring to each parameter of analysis and its corresponding description).

The homogeneity or consistency of a given cluster is measured by the parameter *silhouette*, which gives a value ranging from -1 to 1 (Chen, 2012; Chen et al., 2014c). If the silhouette score of a cluster is very close to the highest value of 1.00, it means that individual nodes in this cluster are tightly connected, suggesting a reliable quality for further review. Emerging trends and abrupt changes in a research field are identified by the *citation burstness* parameter. Citation burst detection provides an effective method of identifying articles that attract increased attention to the underlying research and to trace the development of study focus. For instance, if an article has an abrupt increase in its citation counts in comparison with others, then it is considered to be an article with a citation burst. It is worth noting that a citation burst is indicated by a red tree-ring presented in a particular year. Moreover, *betweenness centrality* (BC) is a parameter that indicates the

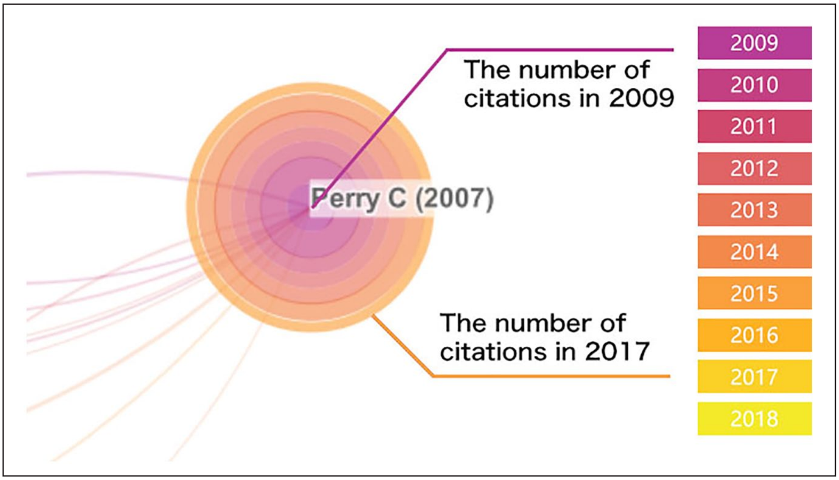

Figure 2. An example of a node, representing a reference published in 2007 (Perry et al., 2007). The thickness of each tree-ring inside of the node indicates the number of citations this reference received across 2009–2018.

achievement of transformative discoveries, thus reflecting the scientific impact of a particular research topic (Chen et al., 2009). In this view, the node with a high BC is considered to play a "bridge" role in different stages of the development of a scientific field (Chen, 2012).

In this study, we used CiteSpace (v.5.3.R10) to perform a co-citation analysis over the last decade of research in VWR, by identifying groups of dominant clusters and most cited references in this field. A total number of 1525 entrances were initially retrieved; from that, we selected the top 15% of most cited publications in each year between 2009 and 2018 (by setting Top N% = 15, time slice = 1), in order to construct and visualize the document co-citation network. This operation was implemented with the aim of controlling the size of a visualized network, which could influence the clarity and complexity of the patterns that we may learn from the visualization (Chen, 2014a). In addition, we restricted the collection of citations to those made in the preceding eight-year period over the next few years, by setting Look Back Year (LBY) to 8; thus ignoring citations made to references more than eight years ago. This procedure was motivated by the aim exploring these emerging trends in the knowledge domain of VWR as well as critical studies in research frontiers based on recent citations, thus bringing the knowledge about VWR up to date. These configuration settings were derived empirically, which tended to identify meaningful thematic patterns, indicated by the visualization clarity, the network modularity, and clusters' silhouette values (Chen & Song, 2019). Consequently, for the resulting co-citation network (617 references), articles with high BC values were analyzed to determine different stages in the evolution of VWR research. Moreover, emerging trends and abrupt changes were detected in terms of references with citation bursts.

3 Results

Figure 3 shows the co-citation network, which contains 617 cited references (namely nodes) and 11 clusters based on the co-citation relationships and network attributes. The citation history is indicated on the basis of the tree-rings of each node, displayed by different colors and thicknesses; nodes with red tree-rings indicate references with citation bursts. The network showed a *Modularity*

Table 1. List of basic terms and parameters of analysis related the use of CiteSpace as a bibliometric tool.

Term	Description
Co-citation network	• A knowledge network represents how frequently two references are cited by other articles simultaneously. For instance, if two references are cited by a third or different articles, there may be a stronger correlation between them (Chen et al., 2014b; Small, 1973). • Co-citation literature represents the knowledge foundation and development of the given field (Chen et al., 2010; Small, 1973).
Cluster	• The synthesized network is divided into clusters of cited references. • Thematic patterns of each cluster are identified based on noun phrases extracted from citing articles' titles and abstracts; then, the most representative noun phrases are further computed to identify the label of the cluster (Chen & Song, 2019).
Modularity Q	• Modularity Q $>$ 0.3 means that the separated social structures in the given field are clearly defined in terms of co-citation clusters (Chen, 2016; Chen et al., 2010).
Silhouette	• Silhouette $>$ 0.5 means that the clustering effects are reasonable, and the level of homogeneity is relatively high, suggesting that each cluster is well matched with each other (Chen, 2016; Chen et al., 2010).
Log-likelihood ratio (LLR) tests	• The LLR tests are considered to recognize labels effectively within the cluster; these labels are used to name clusters with better representativeness (Chen et al., 2010, 2012).
Size	• Size denotes the number of cited references in each cluster. • Clusters with few members tend to be less representative than larger ones, since small clusters are susceptible to the citing behavior of a small number of articles (Chen, 2012).
Betweenness centrality (BC)	• BC value is commonly used as structural metric for qualifying the academic impact of one reference in citation networks (Li & Chen, 2016). • Nodes with high BC (whose BC value $>$ 0.1) tend to identify boundary spanning potentials that may lead to transformative discoveries (Chen, 2017; Chen et al., 2009; Schierz et al., 2010).
Citation Burstness (CB)	• CB is a computational technique that has been used to identify references attracting increased attention to the underlying research and to trace the development of study focus (Chen, 2017; Kleinberg, 2003).
Sigma	• The sigma score is a combinant metric of the BC and the citation burstness of the cited reference (Chen, 2017). • A cited reference with high sigma score reflects its structural and temporal significance (Chen, 2017).

Q value of 0.7297, considered relatively high, indicating that the overall division was clearly defined in terms of clusters (Chen, 2017). Table 2 shows the different clusters into which the co-citation network is divided, listed by their size (the number of cited references in each cluster). Three clusters with few members (no more than 10 cited references) were excluded from further analysis because they tended to be less representative than the larger ones. The homogeneity of each cluster, measured by the *silhouette* parameter, tended to be close or very close to the highest score of 1, suggesting that the references in each cluster were well matched.

In order to correctly examine the time course of a given cluster, a timeline visualization of the co-citation network should be considered in CiteSpace, as shown in Figure 4. In this way, clusters are labeled on the right and arranged vertically in descending order depending on their size. For each cluster, nodes on the horizontal line indicate references in the cluster to which it belongs, and colored curves represent co-citation relationships added in the year of the corresponding color. It is

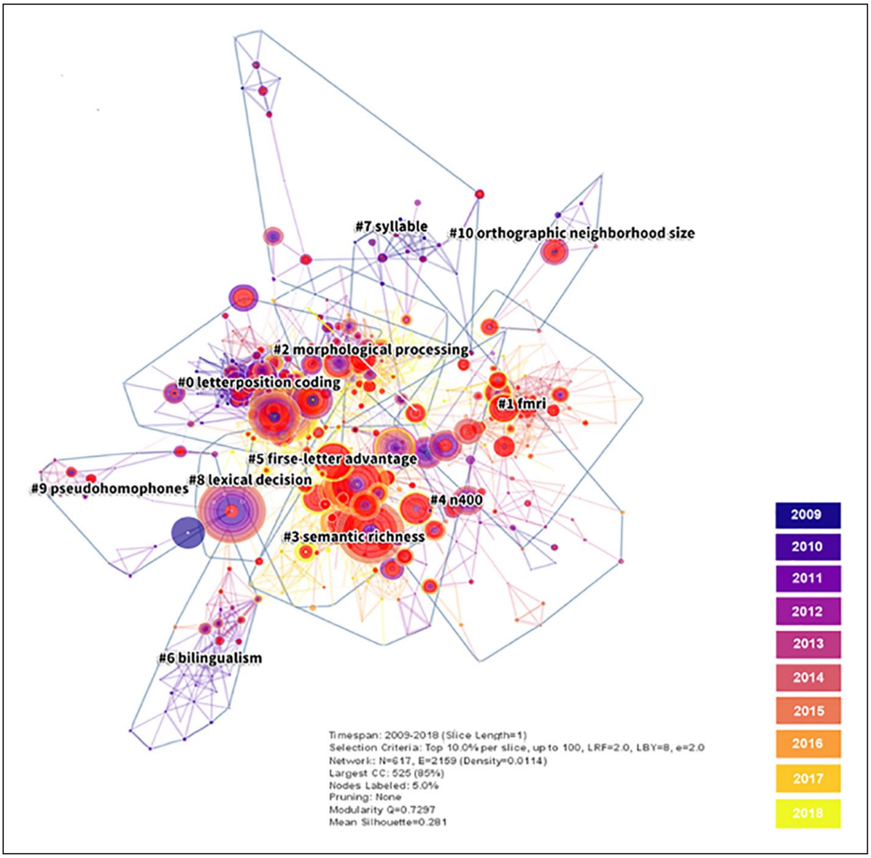

Figure 3. Landscape view of the co-citation network in VWR between 2009 and 2018.

to be noted that years in the horizontal line indicate the time when cited references were published. The visualization of large-size nodes or nodes with red tree-rings indicate influential investigations because they were either highly cited, had citation bursts, or both (Chen, 2017). As shown in the timeline visualization, some clusters have remained active over the past 10 years, such as Cluster #1 and Cluster #2; while others have lasted for a limited number of years, such as Clusters #6 to #10. In addition, Cluster #0 to Cluster #5 were full of large citation tree-rings and had strong citation bursts colored in red, suggesting that these clusters constituted the major and most active research efforts in the VWR knowledge domain during the given period of 2009–2018. It is worth noting that a cluster without a latest node does not mean that there is no latest article in this cluster, but that such a cluster has less influence because only references cited more than a certain number of times can appear in the co-citation network.

It is known that, in scientometrics (a branch of informatics in which the knowledge structure and emerging trends of a given field are evaluated quantitatively), a knowledge base is formed by cited references. In particular, the knowledge base is the collection of references cited by the corresponding articles at the same time; hence, the analysis was conducted in this study on the resulting clusters to identify the knowledge base in the domain of VWR studies (Chen, 2017). In the following sections, we provide a more detailed description of the results obtained across nine different clusters (cluster ID #0, #1, #2, #3, #4, #5, #7, #9, and #10) with their labels extracted from

Table 2. Summary of the clusters into which the co-citation network is divided.

Cluster ID	Size	Silhouette	Median (Year)	Label (LLR)
0	90	0.887	2007	Letter position coding
1	80	0.898	2010	fMRI
2	65	0.916	2010	Morphological processing
3	63	0.84	2010	Semantic richness
4	58	0.925	2008	N400
5	44	0.912	2012	First-letter advantage
6	33	0.992	2006	Bilingualism
7	26	0.99	2004	Syllable
8	21	0.86	2013	Lexical decision
9	18	0.98	2006	Pseudohomophones
10	10	0.994	2005	Orthographic neighborhood size

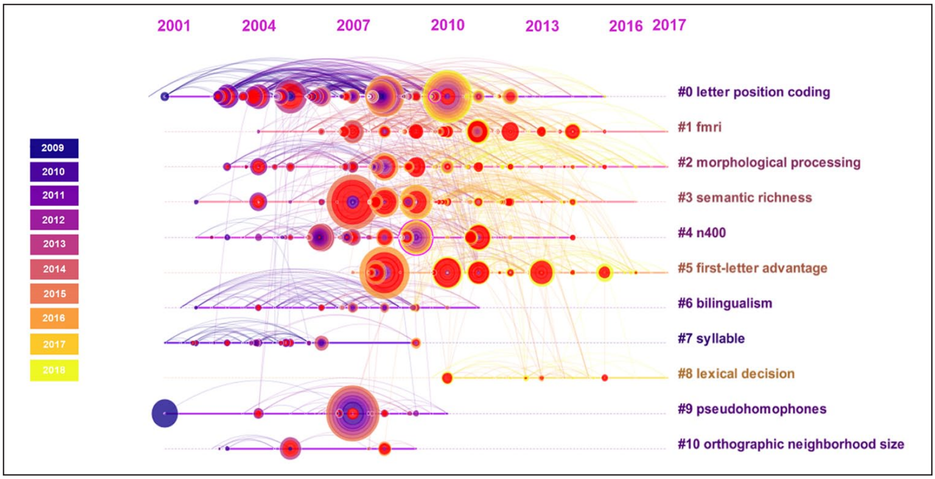

Figure 4. A timeline visualization of the co-citation network in VWR research.

the titles of citing articles of a particular cluster, identified by the log-likelihood ratio test method (LLR) (Chen et al., 2010). The remaining two clusters in this knowledge domain were either short in length (cluster #6) or relatively small in size (cluster #8), and they had few large-sized nodes or nodes with red tree-rings. Thus, we omitted the detailed interpretation of these two clusters.

Cluster interpretation was divided into three parts, in which various entities represented groups of component processes based on their attributes. The first part aimed to determine, based on co-cited references, *what* type of representations are involved in recognizing visual words. More specifically, the content of this part consisted of four aspects, including orthographic coding in VWR (cluster ID #1, #5, #10), phonological recoding in VWR (cluster ID #7, #9), semantic activation during VWR (cluster ID #3), and morphological processing in VWR (cluster ID #2). In addition, the analysis of two other clusters provided the information to answer the questions of *where* and *when* VWR occurs, as they introduced techniques such as functional magnetic resonance imaging (fMRI) (cluster ID #1) and event-related potentials (ERPs) (cluster ID #4). Finally, we focused on cluster members with high frequency or high sigma metric (a combinatorial metric of both structural

Table 3. References with high frequency or sigma metric in cluster #0, related to letter position coding.

Freq.	Sigma	Author (year)	Title	Source
115	1.37	Davis, C. J. (2010)	The spatial coding model of visual word identification	*Psychological Review*
95	1.16	Gomez, P. (2008)	The overlap model: A model of letter position coding	*Psychological Review*
74	1	Grainger, J. (2008)	Cracking the orthographic code: An introduction	*Language and Cognitive Processes*
54	1.51	Perea, M. (2004)	Can CANISO activate CASINO? Transposed-letter similarity effects with nonadjacent letter positions	*Journal of Memory and Language*
30	2.41	Norris, D. (2010)	A stimulus sampling theory of letter identity and order	*Journal of Memory and Language*

centrality and citation bursts of the node), thus showing *how* these studies brought insight into the structure, topography, and temporal flow of lexical information in the study of VWR.

3.1 The "what" of VWR

3.1.1 Orthographic coding in VWR (cluster ID #0, #5, and #10). A printed word is primarily considered to be an orthographic object. For instance, individual words are composed of a string of letters, at least in alphabetical writing systems. Thus, it is generally believed that the spatial arrangement of letters is the "front end" of early visual word processing. Accordingly, the term "orthographic coding" refers to the information on letter positions (where are the constituent letters within a given string?) and letter identities (what are the constituent letters in the string?). Based on this, we used orthographic coding as the starting point of the discussion by interpreting clusters #0, #5, and #10.

It was seen that the largest cluster, *#0 letter position coding*, contained 90 references (see Table 2). It contained a broad range of references addressing the early stages of VWR, letter position, and letter identity, especially based on transposed-letter effects (i.e., the illusion of perceiving "jugde" as "judge"). As illustrated in Figure 3, this cluster has large citation tree-rings and citation bursts, with the majority of references either highly cited or with citation bursts, showing that the question concerning how to present letters and their position had received considerable attention in VWR research over the last decade. The same result can be visualized in the timeline overview shown in Figure 4, from which this cluster remains active over a period of time, roughly between 2003 and 2012. The most cited reference in this period is the study of the spatial coding model (Davis, 2010) (as shown in Table 3). Davis (2010) argues that orthographic representation depends on letter-specific mechanisms of position coding endowed with a certain amount of positional flexibility. Assumptions about the uncertainty of the letter position were also made with regard to the noisy position coding mechanism, such as in the Overlap Model, presented by the second-highest citation in the ranking (Gomez et al., 2008), and the Bayesian Reader Model proposed by Norris (2010), with a sigma metric of 2.41. According to the positional noise assumption, transposed-letter effects reflect the operation of generic noise (i.e., position uncertainty) on the rigid position-coding mechanism of input. In other words, it is likely that the activation of each component letter can extend to adjacent positions. For example, the representation of the *judge* is activated by *g* in the fourth position, and by *g* in the third position. In addition, Perea (2004) proposed that nonadjacent transposed-letter primes can produce

Table 4. References with high frequency and sigma metric in cluster #5, related to first-letter advantage.

Freq.	Sigma	Author (year)	Title	Source
77	1.37	Perry, C. (2010)	Beyond single syllables: Large-scale modeling of reading aloud with the Connectionist Dual Process (CDP++) model	*Cognitive Psychology*
62	1.37	Grainger, J. (2011)	A dual-route approach to orthographic processing	*Frontiers in Psychology*
26	1.3	Grainger, J. (2012)	Evidence for multiple routes in learning to read	*Cognition*
13	1.04	Grainger, J. (2016)	A vision of reading	*Trends in Cognitive Sciences*
7	1	Grainger, J. (2016)	A developmental investigation of the first-letter advantage	*Journal of Experimental Child Psychology*
3	1	Aschenbrenner, A. J. (2017)	The first letter position effect in visual word recognition: The role of spatial attention	*Journal of Experimental Psychology-Human Perception and Performance*

priming effects created by exchanging two nonadjacent letters. For instance, a nonword like *cholocate* is effective at activating the representation of its base word *chocolate*; thus, letter position and identity are coded based on flexible perceptual schemes adapted for orthographic processing. Grainger (2008) listed a subset of current approaches to understand orthographic processing in reading and to discuss how the constituent letters are coded during the earliest processing of recognizing visual words. Although these extensive empirical models can only be judged under the condition of a certain dataset, they have the capability to demonstrate that transposed-letter effects are orthographic in nature. Therefore, models of orthographic coding show that each component in the letter strings is a key element for orthographic processing and that the letter-position coding mechanism determines the nature and identity of the orthographic code.

Cluster #5, labeled as *first-letter advantage* and containing 44 members, has become more prevalent since 2008, as shown in Figure 4. The first-letter advantage refers to the fact that the first letter is more important than the rest of the letters for letter position coding. Apart from summarizing the high-impact contributions (Grainger et al., 2012; Grainger & Ziegler, 2011; Perry et al., 2010), this cluster was also interpreted by discussing some of the recent cited members (Aschenbrenner et al., 2017; Grainger, Bertrand et al., 2016; Grainger, Dufau et al., 2016), shown in Table 4. Two studies with high frequency, conducted by Jonathan Grainger, should be considered: one focusing on the question of how the visual constraints influence orthographic processing in skilled reading (Grainger & Ziegler, 2011), and the other on the development of this skill in beginning readers (Grainger et al., 2012). According to the spatial coding model, the "dynamic end-letter marking" (Davis, 2010) assigns higher weights to letter-to-word connections for initial letter and final letter across a word. This mechanism has also been applied by a dual-route approach of skilled reading (Grainger & Ziegler, 2011), a multiple-route model of word learning (Grainger et al., 2012), and a new connectionist dual process (CDP++) model (Perry et al., 2010). According to these models, the development of parallel letter processing has been postulated to cause a transition from strictly serial fashion to parallel mapping of letters. Indeed, if all letters became available simultaneously, one could expect the accuracy to increase the chance of identifying the initial letters in strings earlier compared to the later ones. However, parallel processing models that account for the first-letter advantage, discussed by the above studies, leave an open question of why the initial letter position has such "priority" during processing. To further explore this issue, Grainger (2016a) and Grainger (2016b) supported the modified receptive fields hypothesis (MRFH), stating that aspects related to low-level perceptual processing optimize the processing of the initial letter of words from an adaptive modification. MRFH suggests that increased reading ability can be associated with the degree of attention paid to the first letter position of words. Moreover, compared with the above models, Aschenbrenner et al. (2017) incorporated attentional processes into computational analysis, revealing that the additional advantage for the initial letter position is explained by the role of visual spatial attention, and thus introduced the attentional dynamics in models of recognizing visual words.

Cluster #10, *orthographic neighborhood size*, consisted of 10 references. The analysis through clusters #0 and #5 discussed questions regarding the computation of letter position with a printed word and its performance. The development of orthographic processing during reading, probably the next key step in the processes carried out in VWR, is discussed by interpreting cluster #10. Two references (Share, 2008; Ziegler & Goswami, 2005) with strong citation bursts, as visualized in the timeline overview in Figure 4, were emphasized in the analysis. Most influential models of VWR, such as the dual route model, postulate the existence of two independent routes to read a printed word: a lexical (direct) route and a nonlexical (sublexical) or grapheme-to-phoneme route (GPC). However, cross-language disparity in the use of these two routes has been demonstrated over the last decade. According to the psycholinguistic grain size theory (Ziegler & Goswami, 2005), skilled English readers rely on the whole word when reading, thus using the direct route; whereas in more transparent languages, such as Spanish, Italian, or even German, readers rely on smaller units (e.g., transposing syllables or letters to phonemes), hence using the indirect route. Moreover, for adult samples, English readers show lower naming latencies when reading words or nonwords with many orthographic neighbors than when reading words with few orthographic neighbors. On the contrary, no differences exist in the response latencies of German readers to either words or nonwords depending on the neighborhood size. The different response latencies of reading English and German points out that English readers show more facilitation by orthographic neighbors than German readers (Ziegler et al., 2001), thus denoting that their reading relies more on whole-word visual recognition than in GPC processes. Hence, the orthographic depth and grain size tends to underlie the cross-language disparity in orthographic neighborhood size effects. However, one of the challenges in conducting cross-language research is to match item sets across languages on factors such as word structure, length, and meaning. Although these item sets have been tackled by using cognates or identical words in previous studies (mostly English vs. German), Share (2008) argued that a universal reading model is required to control for other factors influencing reading development, especially orthographic neighborhood size and frequency.

3.1.2 Phonological recoding in VWR (cluster ID #7 and #9). It is supposed that phonological information influences early aspects of word processing. Although there is an agreement regarding the early involvement of phonological processes in reading, research on how phonological representations are processed during the early stages of reading remains inconclusive. Over the last decade, attempts to explain the role of phonology in reading have revolved around the processing of polysyllabic words and pronounceable nonwords, as interpreted in clusters #9 and #7, respectively.

Cluster #9, labeled as *pseudohomophones*, encompassed 18 cited members. The pseudohomophone effect reflects that pronounceable nonwords that sound like words (pseudohomophones) are more difficult to reject as nonwords than other orthographically pronounceable legal nonwords. This effect demonstrates that pseudohomophones are phonologically decoded, showing that phonological rules are applied to the initial orthographic form-based stimulus. This and other effects have been explained by computational dual route models of VWR, including phonological

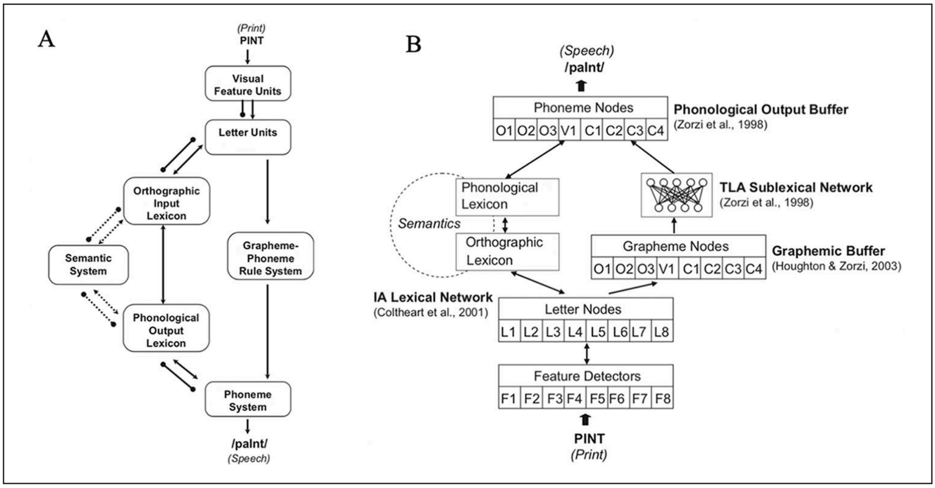

Figure 5. Left panel A. The DRC model of visual word recognition (Coltheart et al., 2001). The dashed lines depict the lexical-semantic pathway that is not implemented. Right panel B. CDP+ model (Perry et al., 2007). O = onset; V = vowel; C = coda; TLA = two-layer assembly; IA = interactive activation; L = letter; F = feature.

influences. The most prominent contributions in this cluster included two localist frameworks: a dual-route cascaded model (DRC) (Coltheart et al., 2001) and a new connectionist dual process (CDP+) model (Perry et al., 2007), ranking top citations among members of this cluster. As can be seen in Figure 5, the common feature of the two models is that both have a dual route architecture comprising a lexical route and a nonlexical route.

The lexical route, considered in both models, contains orthographic input lexicon (memory representations for word spellings) and phonological output lexicon (memory representations for word pronunciations). This route can be used to generate correct pronunciations for known words (real words) and irregular (inconsistent) words, but not for nonwords. In contrast, the nonlexical route enables the pronunciation of regular (consistent) words and nonwords, but not for irregular words. The key difference between DRC and CDP+ is that the nonlexical route operates on different computational principles in each model. The nonlexical route in the CDP+ model contains the graphemic buffer and a two-layer phonological network (TLA), which results in a more accurate performance of reading nonwords in this model. As shown in Figure 5, orthographic information in the connectionist network is structured into the graphosyllable template, and then a parallel distributed processing activates TLA and generates a plausible sublexical phonological representation. This is not considered in the DRC model. Therefore, the CDP+ model suggests that mappings between onset, vowel, and coda units are direct. These localist models, therefore, present basic reading processes to understand how sublexical knowledge is recruited in the phonological lexicon when reading novel words.

Cluster #7, with 26 members and a high silhouette value of 0.99, was labeled as *syllable*. In this cluster, the nature of syllable processing during the recognition of polysyllabic words is discussed, showing that phonology can indeed influence VWR. Previous research derived from the DRC and CDP+ models mentioned previously, considers VWR as primarily driven by the analysis of orthographic information (a direct orthographic route). In contrast, phonological mapping (an indirect phonologically mediated route) is considered nonessential and secondary during recognition. These models deal exclusively with the processing of monosyllabic words, and thus

Table 5. References with high frequency or sigma metric in cluster #7, related to syllable.

Freq.	Sigma	Author (year)	Title	Source
38	1	Rastle, K. (2006)	Masked phonological priming effects in English: Are they real? Do they matter?	*Cognitive Psychology*
24	1.36	Carreiras, M. (2005)	Sequential effects of phonological priming in visual word recognition	*Psychological Science*
24	1.16	Conrad, M. (2009)	Syllables and bigrams: Orthographic redundancy and syllabic units affect visual word recognition at different processing levels	*Journal of Experimental Psychology-Human Perception and Performance*
19	1.17	Alvarez, C. (2004)	Are syllables phonological units in visual word recognition?	*Language and Cognitive Processes*

ignore syllabic representation. However, a serious limitation has been detected in previous research, given that these models deal exclusively with the processing of monosyllabic words, and thus ignore syllabic representation. As shown in Table 5, high-impact contributions in cluster #7 included masked phonological priming experiments in Spanish (Alvarez et al., 2004), French (Carreiras et al., 2005), and English (Rastle & Brysbaert, 2006), suggesting that syllable effects should be attributed to phonological representations in nature. Therefore, phonological processing involving the emergence of syllables at an intermediate layer between the sublexical level (letters, graphemes, and phonemes) and the lexical level (whole word forms) (Conrad et al., 2009) is an important step in VWR.

3.1.3 Semantic activation during VWR (cluster ID #3). Computational models, such as DRC, CDP+, and CDP++, suggest that the process of VWR involves both sublexical and lexical routes to map graphemes in phonemes. However, these models fail to pinpoint the specific role of semantic processing during VWR. In this section, we reviewed the issue of the influence of semantic effects on VWR by interpreting cluster #3.

Cluster #3, labeled as *semantic richness*, consisted of 63 cited references. The semantic richness effect refers to the fact that words associated with relatively more semantic information, considered as semantically rich words, are recognized faster. Several dimensions can reflect the richness of semantic representations. Typically, a word can be recognized faster, for example, when its referent is associated with many semantic features (*the number of semantic features*, Pexman et al., 2003), when it has a dense semantic neighborhood (*the semantic neighborhood density*, Buchanan et al., 2001), when it is related to multiple meanings (*the number of senses*, Yap et al., 2011), when it elicits more associates (*the number of distinct first associates*, Dunabeitia et al., 2008), when it evokes much mental imagery (*imageability*, Cortese & Fugett, 2004), or when it has emotional content (*emotional valence*, Siakaluk et al., 2008). Notably, although semantics is the key notion within the topic of embodied cognition, it does not appear as a cluster in VWR research, since articles focused on embodiment theories belong to other fields of research such as mental models.

Based on the timeline visualization of this cluster (shown in Figure 4), we reviewed five key contributions (Balota et al., 2007; Brysbaert & New, 2009; Keuleers et al., 2012; Yap & Balota, 2009; Yarkoni et al., 2008), with large citation tree-rings and citation bursts that were published in a highly active period from 2007 to 2012 (see also Table 6). A number of previous studies (e.g., Buchanan et al., 2001; Cortese & Fugett, 2004; Pexman et al., 2008; Siakaluk et al., 2008) attempted to capture the impact of semantic richness effects on VWR across different tasks. In order to

Table 6. References with high frequency or sigma metric in cluster #3, related to semantic richness.

Freq.	Sigma	Author (year)	Title	Source
120	1.19	Balota, D. A. (2007)	The English Lexicon Project	*Behavior Research Methods*
75	2.07	Brysbaert, M. (2009)	Moving beyond Kucera and Francis: A critical evaluation of current word frequency norms and the introduction of a new and improved word frequency measure for American English	*Behavior Research Methods*
74	1	Yarkoni, T. (2008)	Moving beyond Coltheart's N: A new measure of orthographic similarity	*Psychonomic Bulletin & Review*
40	1.29	Yap, M. J. (2009)	Visual word recognition of multisyllabic words	*Journal of Memory and Language*
20	1.77	Keuleers, E. (2012)	The British Lexicon Project: Lexical decision data for 28,730 monosyllabic and disyllabic English words	*Behavior Research Methods*

determine and compare individual differences in VWR, these studies used trial-level data extracted from online databases with behavioral measures for English words and nonwords (i.e., lexical decision). However, other databases such as the English Lexicon Project, the database with the highest number of citations in this cluster, have gained more popularity over the last decade (Balota et al., 2007). Furthermore, based on various databases, the British Lexicon Project (Keuleers et al., 2012) is presented to offer researchers with a new dataset for mixed effects analyses and mathematical models. Subsequent experiments (Cop et al., 2015; Woollams et al., 2016; Yap et al., 2015; Yap et al., 2012) extended earlier studies to support the multidimensional nature of semantic richness by using linear mixed model analysis, controlling the influence of correlated lexical variables. Among these variables, two measures have drawn much attention over the last decade; the log frequency (Brysbaert & New, 2009), which considers sublexical word frequency measures (numbers of morphemes and letters), and the orthographic (Yarkoni et al., 2008) and phonological (Yap & Balota, 2009) Levenshtein distance (i.e., orthographic and phonological neighborhood size measures). It is argued that semantic representations play a fundamental role in VWR. Nevertheless, the question about semantic influences during earlier stages of VWR, related to lexical-level representations (i.e., orthographic and phonological representations), remains controversial (Pexman et al., 2002; Yap et al., 2015).

3.1.4 Morphological processing in VWR (cluster ID #2). Cluster #2, related to *morphological processing*, was the third largest cluster with 65 cited references. As shown in Figure 4, the nine-year period ranging from 2004 to 2012 was full of high-impact contributions within this cluster, which accounted for two major theoretical positions regarding the influence of morphological complexity in word processing: morpho-orthographic segmentation and morpho-semantic processing. Therefore, we reviewed five cited references that are highly ranked either by their citation counts (Feldman et al., 2009; Rastle et al., 2004; Rastle & Davis, 2008) or by their sigma scores (Baayen et al., 2011; Beyersmann et al., 2012), to discuss the cognitive mechanism of morphological processing (see Table 7). Masked morphological priming studies in adults conducted by Rastle and her colleagues (Rastle et al., 2004; Rastle & Davis, 2008) reported that morphologically complex words can be decomposed into their morphemic constituents at the early stages of processing. Rastle and Davis (2008) claimed that early morpho-orthographic segmentation "allows rapid access to the meanings of morphologically structured stimuli *most of the time*" (p. 950). Conversely, these key

Table 7. References with high frequency or sigma metric in cluster #2, related to morphological processing.

Freq.	Sigma	Author (year)	Title	Source
64	1.15	Rastle, K. (2008)	Morphological decomposition based on the analysis of orthography	*Language and Cognitive Processes*
49	1.25	Feldman, L. B. (2009)	Early morphological processing is morphosemantic and not simply morpho-orthographic: A violation of form-then-meaning accounts of word recognition	*Psychonomic Bulletin & Review*
40	1.22	Rastle, K. (2004)	The broth in my brother's brothel: Morpho-orthographic segmentation in visual word recognition	*Psychonomic Bulletin & Review*
29	1.28	Baayen, R. H. (2011)	An amorphous model for morphological processing in visual comprehension based on naive discriminative learning	*Psychological Review*
11	1.25	Beyersmann, E. (2012)	Morphological processing during visual word recognition in developing readers: Evidence from masked priming	*Quarterly Journal of Experimental Psychology*

shreds of evidence were challenged by Baayen et al. (2011), who criticized prior masked priming studies. They pointed out that priming effects tested in pseudo-suffixed priming conditions were obtained because most prime words were in fact semantically transparent. However, Beyersmann et al. (2016) refuted Baayen's explanation with a set of entirely semantically opaque items, supporting the evidence for morpho-orthographic segmentation. Thus, the decomposition of morphologically complex words underlies the cognitive mechanism of morphological processing. Regarding morpho-semantic processing, prior research has raised two opposing views on the activation of morpho-semantics during processing of morphologically complex words. One of the assumptions is form-then-meaning, which proposes that morpho-semantic processing occurs subsequent to initial form-driven morpho-orthographic processing (Beyersmann et al., 2012, 2016; Rastle & Davis, 2008; Rastle et al., 2004). The other assumption is form-with-meaning, resulting from the observation that semantically transparent and opaque primes yield varying degrees of priming (Andrews & Lo, 2013; Feldman et al., 2009). These studies provide strong evidence that morphology functions as a linguistic aspect, exerting an important influence during VWR.

3.2 The "where" and "when" of VWR?

In section 3.1, we focused on the major findings over the last decade by reviewing behavioral investigations to discuss questions regarding what types of representations are stored in a printed word and how they are perceived and influence early aspects of overall word identification. In addition, spatial and temporal measurements should be considered, showing when and where the internal representations of written language are activated, thus providing information about the neural basis of VWR. Given that a highly organized brain system is essential for VWR, which enables the integration of orthographic, phonological, and semantic information, the answer to "when" and "where" questions seem to be useful in pursuing the nature of the mental representations acquired for written word forms as well as how the temporal sequence of their processing is carried out. In this section, we review various studies using fMRI and electrophysiological

Table 8. References with high frequency or sigma metric in cluster #1, related to use of fMRi in VWR research.

Freq.	Sigma	Author (year)	Title	Source
59	1.39	Price, C. J. (2011)	The interactive account of ventral occipitotemporal contributions to reading	*Trends in Cognitive Sciences*
55	1.57	Dehaene, S. (2011)	The unique role of the visual word form area in reading	*Trends in Cognitive Sciences*
55	1.45	Vinckier, F. (2007)	Hierarchical coding of letter strings in the ventral stream: Dissecting the inner organization of the visual word-form system	*Neuron*
42	1.46	Price, C. J. (2012)	A review and synthesis of the first 20 years of PET and fMRI studies of heard speech, spoken language and reading	*Neuroimage*
42	1.32	Carreiras, M. (2014)	The what, when, where, and how of visual word recognition	*Trends in Cognitive Sciences*
27	1.8	Taylor, J. S. H. (2013)	Can cognitive models explain brain activation during word and pseudoword reading? A Meta-analysis of 36 neuroimaging studies	*Psychological Bulletin*

measures, such as ERPs, aimed at identifying the location of multiple brain regions activated during VWR as well as the timing of such brain activities.

3.2.1 The "where" of VWR: fMRI studies (cluster ID #1). Cluster #1, fMRI, containing 80 cited references, was the second largest cluster. The time visualization revealed that this cluster remained active from 2007 to 2014, with high-profile references in terms of large-sized nodes or nodes with red tree-rings (in Figure 4). Therefore, we reviewed six influential studies in this period (Carreiras et al., 2014; Dehaene & Cohen, 2011; Price, 2012; Price & Devlin, 2011; Taylor et al., 2013; Vinckier et al., 2007) based on citation counts or sigma metrics (shown in Table 8). It is argued that the cortical system underlying the reading process in the left hemisphere includes three functionally specialized pathways: (i) the left dorsal pathway proposed by Taylor et al. (2013), which involves the left posterior temporal cortex (classically termed Wernicke's area), and is proven to be associated with the map of orthography into phonology (i.e., GPC decoding); (ii) a left ventral pathway, which is believed to be involved in visual-orthographic word recognition by integrating sensory input with top-down feedback from phonological and semantic areas (Price & Devlin, 2011); and (iii) the left inferior frontal cortex around the left posterior inferior frontal cortex (classically termed Broca's area) presented by Price (2012). Broca's area is linked to speech perception, comprehension, and production. In addition to these pathways, this cluster discussed the issue related to the putative visual word form area (pVWFA), which has been hotly debated among researchers in the last decade. Therefore, we focused on the major theoretical positions regarding the pVWFA (Carreiras et al., 2014; Dehaene & Cohen, 2011; Price & Devlin, 2011; Vinckier et al., 2007), which mainly differ in how specialized the pVWFA is and how involved it is in top-down versus bottom-up information processes. Dehaene and Cohen (2011) and Vinckier et al. (2007) proposed that pVWFA, as a prelexical, reproducible site specific for visual orthographic coding, that develops an efficient bottom-up hierarchy process of computing and storing strictly prelexical visual orthographic representations, such as letters, bigrams, and morphemes. In contrast, an alternative "interactive" account (Carreiras et al., 2014; Price & Devlin, 2011) posited that the activation of the pVWFA is modulated by higher-level top-down representations, such as phonological,

Table 9. References with high frequency or sigma metric in cluster #4, related to N400.

Freq.	Sigma	Author (year)	Title	Source
80	1	Grainger, J. (2009)	Watching the word go by: On the time-course of component processes in visual word recognition	*Language and Linguistics Compass*
65	1.24	Kutas, M. (2011)	Thirty years and counting: Finding meaning in the N400 component of the Event-Related Brain Potential (ERP)	*Annual Review of Psychology*
64	1	Holcomb, P. J. (2006)	On the time course of visual word recognition: An event-related potential investigation using masked repetition priming	*Journal of Cognitive Neuroscience*
34	1.62	Laszlo, S. (2011)	The N400 as a snapshot of interactive processing: Evidence from regression analyses of orthographic neighbor and lexical associate effects	*Psychophysiology*
14	1.13	Chauncey, K. (2008)	Effects of stimulus font and size on masked repetition priming: An event-related potentials (ERP) investigation	*Language and Cognitive Processes*

morphological, and semantic representations. Hence, the dispute among these theories lies in whether higher-level linguistic representations modulate early perceptual processing of orthographic information; nonetheless, even if they do, the extent to which high-level processes modulate perceptual processing is still unknown. Thus, the existing knowledge of how reading circuits operate on the brain is far from being fully understood.

3.2.2 The "when" of VWR: ERPs studies (cluster ID #4). In the past decade, tracking the time course of word processing, ranging from low-level visual perception to phonological and semantic representations, by using time-sensitive methods such as EEG/MEG has been crucial for the understanding of when and how these representations are activated and how they interact during VWR.

Table 9 shows the references with the highest number of citations or sigma values (Chauncey et al., 2008; Grainger & Holcomb, 2009; Holcomb & Grainger, 2006; Kutas & Federmeier, 2011; Laszlo & Federmeier, 2011) within cluster #4, labeled as *N400*. It is reasonable to start a section on ERPs by discussing the VWR literature focused on the N400, since this is probably the most well-known ERP component indicative of functional aspects during the lexico-semantic processing of words. Thus, ERP research on VWR, mainly active between 2006 and 2011 (see Figure 4), tends to engage in the modulation of N250 and N400 components during word processing, as related to orthographic and semantic processes. The Bimodal Interactive Activation Model (Grainger & Holcomb, 2009) stated that N250 is one of the earliest components related to word identification, a neural response with a right posterior scalp distribution elicited during masked repetition priming conditions (Holcomb & Grainger, 2006). According to Chauncey et al. (2008), the N250 priming effect reflects prelexical orthographic processing during the form-meaning interface. The N250 response is followed by the N400, a negative component, peaking around 400 ms post-stimulus onset with a posterior scalp distribution, which displays many characteristics related to contextual and lexical meaning. Hence, N400 can be identified as the time course associated with semantic processing (Grainger & Holcomb, 2009; Kutas & Federmeier, 2011). Specifically, reductions in N400 amplitude, as a consequence of repetition and specific predictions in higher-level sentence contexts, are observed in different types of stimuli, including words, pseudowords (Kutas &

Federmeier, 2011), and even illegal consonant clusters (Laszlo & Federmeier, 2011). Therefore, such reduction suggests that although form-based information is mapped onto meaning in the corresponding time window, neural processing is not restricted to one particular stimulus condition. Notably, Laszlo and Federmeier (2011) argued that the N400 component, as a "snapshot" of late orthographic and early semantic processing, reflects an activation flowing through all levels of representation occurring in parallel. The modulation of the N400 component, related to task-independent mechanisms both for word processing in and out of constraining context and for different types of stimuli, is indicative of how our brain processes printed-word input under different circumstances.

3.3 The "how" of VWR: Interactivity among different representational systems

In this section, we focused on one of the most debated topics in VWR research, namely, how different sublexical units are assembled to be recognized as a whole word, a question that directly concerns interactivity processes and the distinction between top-down and bottom-up processing. Bottom-up word-based processing, in particular, suggests that purely orthographic information is considered to determine a significant part of word identification, a process that is, in principle, uninfluenced by the activation of other higher-level representations. However, top-down processing indicates that higher-ordered linguistic representations exert top-down influences on orthographic processing (Carreiras et al., 2014). The demarcation between top-down and bottom-up processing can be further classified into three questions:

- Does phonological information spread further down to form-level processing?
- Does semantic information proceed in a top-down feedback manner to influence early orthographic processing?
- Does morpho-semantics play an important role in the early stages of word recognition?

In the following section, the most cited references in the VWR domain were analyzed to investigate the interactivity among different types of representations during VWR, based on the parameter of *frequency* in the co-citation network. In addition, the parameters of *BC* and *burst detection* were considered to clarify the aforementioned debate (top-down vs. bottom-up) and reveal the emerging trends of VWR research.

*3.3.1 Interactivity of the reading process (*frequency*).* Interactivity refers to the communication between different levels of representations during the processing of word recognition. Table 10 shows a rank list of the top five highly cited references within the co-citation network, which are generally considered as key studies in VWR, based on their significant contribution (according to their citation counts) during the last decade (Chen, 2012). As can be seen in the table, three highly cited references are located in the orthographic information section. The most frequently cited work over the past decades is a nested computational model of VWR, CDP+ (Perry et al., 2007) with 121 citations, sharing the same assumption about localist letter and word processing with the overlap model (Gomez et al., 2008) and the spatial coding model (Davis, 2010). However, according to the CDP+, the mapping between graphemes and phonemes is direct and less dispersed than the mapping between letters and phonemes, which suggests that prelexical orthographic representations must connect with phonological representation in the early stage during word identification. The other two highly cited references introduce two important tools that are widely used in growing research to investigate the communication between levels of processing and to prove interactivity during VWR. The English Lexicon Project presented by Balota et al. (2007) is one of the

Table 10. Top five highly cited references in visual word recognition.

Freq.	Author (year)	Title	Source	Cluster
121	Perry, C. (2007)	Nested incremental modeling in the development of computational theories: The CDP+ model of reading aloud	*Psychological Review*	9 (pseudohomophones)
120	Balota, D. A. (2007)	The English Lexicon Project	*Behavior Research Methods*	3 (semantic richness)
115	Davis, C. J. (2010)	The spatial coding model of visual word identification	*Psychological Review*	0 (letter position coding)
113	Baayen, R. H. (2008)	Mixed-effects modeling with crossed random effects for subjects and items	*Journal of Memory and Language*	5 (first-letter advantage)
95	Gomez, P. (2008)	The overlap model: A model of letter position coding	*Psychological Review*	0 (letter position coding)

tools that is highly used. Numerous studies have harnessed the power of this database, which contains trial-level data for approximately four million word-recognition trials, sampled across thousands of subjects, to estimate detectable individual differences in VWR (as discussed in section 3.1.3). The other tool is the method that uses linear mixed effects regression models to account for participant and item variance (Baayen et al., 2008). In a nutshell, more innovative studies are expected to explore the interactivity among different types of representations and the operations of how they are processed during VWR; although some existing references at the cumulative stages of collecting citations might have a greater influence in the future.

*3.3.2 Groundbreaking models in VWR (*BC*).* In the co-citation network of analysis, nodes with high BC values (BC value > 0.1) indicate that they play the role of broker (or gatekeeper) in bridging nodes and subdomains of VWR research (Abbasi et al., 2012) and lead to transformative discoveries in specific research areas (Chen et al., 2009). In particular, we focused on two main references (Table 11) showing high scores of BC, namely "A stimulus sampling theory of letter identity and order" (Norris et al., 2010), with the highest *BC* score (0.16), and grouped within the cluster #0 (letter position coding), and "Watching the word go by: On the time-course of component processes in VWR" (Grainger & Holcomb, 2009), second in the ranking with a score of *BC* of 0.12, and located in cluster #4 (N400).

As indicated in Table 11, the Bayesian Reader model presented by Norris et al. (2010), connects cluster #0 (letter position coding), #2 (morphological processing), #3 (semantic richness), #5 (first-letter advantage), and #6 (bilingualism). This suggests that sequential representation of letter position cannot map onto lexical representations directly and unambiguously. Moreover, the Bayesian Reader model also refers to the "leakage" effect, which means that substituting a letter with an adjacent one in the prime stimulus initiates significant facilitation. In other words, letter identity and letter position information are accumulated simultaneously during the processing of VWR, showing parallel, independent word identification.

The research conducted by Grainger and Holcomb (2009) bridges multiple studies grouped in cluster #0 (letter position coding), #1 (fMRI), #2 (morphological processing), and #5 (first-letter advantage), presenting a theoretical framework for VWR. In particular, the bi-model interactive-activation model (BIAM) accounts for how different types of representations interact and affect the

Table 11. Key studies in the co-citation network, presenting groundbreaking models and connecting different strands of research across the field of VWR.

BC	Author	Title	Source	Connected Clusters
0.16	Norris, D. (2010)	A stimulus sampling theory of letter identity and order	*Journal of Memory and Language*	Cluster #0 letter position coding Cluster #2 morphological processing Cluster #3 semantic richness Cluster #5 first-letter advantage Cluster #6 bilingualism
0.12	Grainger, J. (2009)	Watching the word go by: On the time-course of component processes in visual word recognition	*Language and Linguistics Compass*	Cluster #0 letter position coding Cluster #1 fMRI Cluster #2 morphological processing Cluster #5 first-letter advantage

transition from visual feature extraction to semantic activation and specify the relative time course of these processing stages. The BIAM has supported evidence for early influences of semantics on the level of visual orthographic representations, in line with previous studies investigating morphological priming that stated form-with-meaning models (Andrews & Lo, 2013; Feldman et al., 2009). Moreover, BIAM suggests that semantic activation begins when a word is presented visually a sufficient number of times, establishing a lexical representation. Therefore, this model sheds light on the top-down processing method for future research and paves the way for formulating a general account for word identification.

To summarize, both studies bridge various strands of research grouped across different clusters, stating the interactivity between low and high levels of linguistic information at different processing stages, and providing an intuitive insight for the development of future research in VWR.

*3.3.3 Top-down versus bottom-up debate and new trends in VWR research (*citation burst*).* A citation burst is characterized by two attributes: the intensity of its burst property and the impact duration of its burst lasting, pointing to the likelihood that the VWR domain has laid or is laying emphasis on the underlying research (Chen et al., 2014c). Accordingly, this section is concerned with the ones with the strongest bursts in the group of references, showing that their citations peaked over a given time period, and the burst group with an end year of 2018, signifying that the impact and popularity of these references and their research topics have the potential to draw more attention in the future (Wang et al., 2018).

"Rising" and "falling" of orthographic representation (abrupt changes in citation). The abrupt change of a reference, by definition, indicates that its citation increased rapidly within a short period and it helped to find the research topics abruptly increased over time (Chen, 2012). The top three references with the strongest bursts over the last decade are shown in Table 12. It is evident that all these references published in 2004 are in cluster #0 and are found to have subsequent citation bursts since 2009. In other words, studies concerning the encoding of letter position within a word began to receive more attention in VWR research between 2009 and 2012. However, researchers seemed to lose interest in the exploration of orthographic representation. Thus, the question is, what caused this rising and falling? The abrupt changes can be associated with the reasons attributed to internal and external factors (Chen, 2006). Internal factors include discoveries and major breakthroughs within the field, whereas external factors may provoke researchers to study VWR from a completely new angle.

Table 12. The top three ranked references by strengths of citation burst.

References	**Citation burst**					**Cluster**
	Year	Strength	Begin	End	Duration (2009–2018)	
Grainger, J. (2004)	2004	13.8924	2009	2011		0
Perea, M. (2004)	2004	12.6091	2009	2012		0
Schoonbaert, S. (2004)	2004	10.2558	2009	2012		0

As mentioned in section 3.1.1, the manner in which letter position is encoded determines the orthographical similarity between different letter strings, which then impacts different models, explaining how lexical information is stored and subsequently retrieved. Thus, the method of coding letter position seems to be a critical component of any computational model of VWR. One of the leading schemes for coding letter position, as shown in Table 12, is the open-bigram model (Grainger & van Heuven, 2004), based on the assumption that a letter string is coded with its local context with ordered letter pairs. Notably, Schoonbaert and Grainger (2004) supported the evidence for the special status of exterior letters, which means that exterior letters are endowed with greater weight than interior ones in the computation of orthographic input coding. Moreover, it is worth mentioning that transposed-letter effects are not limited to adjacent letters. Perea and Lupker (2004) reported that transposed-letter effects can be obtained with the transposition of noncongruous interior letters. It was found that the common theme in these studies is parallel letter processing. Based on this, the following models have been provided to support the interpretation of data from a variety of experiments, such as the overlap model (Gomez et al., 2008) and the spatial coding model (Davis, 2010), which we reviewed as the most cited references in the VWR domain. Thus, the top three references shown in Table 12 provide datasets and empirical findings with the following highly cited references, which might be the internal reason why the listing references in Table 12 have received the steepest increase in citations over the period from 2009 through 2012. However, these models focus on orthographic coding without accounting for the interaction of this process with phonological, morphological, and semantic levels. Failing to consider other representations might be the external factors leading to the development of modeling letter position coding with less impact since 2012.

Emerging trends in the development of VWR. Table 13 arranges the references that had the most recent citation bursts, from 2013 onward, which continued until 2018. Instead of reviewing all listing references, we focused on the more influential ones with stronger bursts in the group of references that started to burst in 2013, 2015, and 2016. Therefore, nine selected references are examined in further detail in Table 13.

Among the references, with recent citation bursts since 2013, the strongest burst is associated with a masked priming study conducted by Feldman (2009), which observes different degrees of priming yielded between transparent and opaque morphologically related primes. This finding thus provides evidence for influences of semantic similarity on early stages of morphological processing and supports the position of form-then-meaning models (mentioned in section 3.1.1, *morphological representation*). The second reference with the strongest citation burst (Wheat et al., 2010) shows stronger priming responses to pseudohomophones than to orthographic control primes in brain regions, including the pars opercularis of the left inferior frontal gyrus and the precentral gyrus and, more importantly, within the first 100 ms of target word onset. This finding suggests

Table 13. A summary list of references with citation burst.

References	**Citation Burst**			
	Strength	Begin	End	Duration (2009–2018)
Feldman, L. B. (2009)	5.6883	2013	2018	
Wheat, K. L. (2010)	5.5946	2013	2018	
Laszlo, S. (2011)	5.3001	2013	2018	
Barr, D. J. (2013)	18.8655	2015	2018	
Carreiras, M. (2014)	15.5402	2015	2018	
Keuleers, E. (2010)	11.8182	2015	2018	
Keuleers, E. (2012)	8.5585	2015	2018	
Bates, D. (2015)	19.081	2016	2018	
Van Heuven, W. (2014)	9.2711	2016	2018	

that phonological information exerts an influence on very early aspects of the VWR process. The third reference with citation burst starting in 2013 is an ERP study (Laszlo & Federmeier, 2011), examining the time course of the impact of several variables on neurophysiological responses. This work shows that the N400 amplitude is influenced by the orthographic neighborhood size of the stimulus. Thus, Laszlo and Federmeier (2011) concluded that the initial activation of a printed word is influenced not only by its semantic representation but also by the meaning of its orthographic neighbors.

What these studies have in common is the focus on the evidence that high-level linguistic representations, including morphological, phonological, and semantic representations, take part in the process of VWR at an early stage, rather than being initially identified on the basis of orthography alone, and thus support top-down processing. In accordance with this, the study of Carreiras et al. (2014), with a strong citation burst since 2015, reviews important accounts regarding the demarcation between top-down and bottom-up processing. This review paper supports a fully interactive processing system whereby early perceptual orthographic processing is prone to be modulated by higher-ordered linguistic information.

Among other references with citation bursts, those starting in 2015 are led by a highly cited reference (Barr et al., 2013) published in 2013, with 2,154 citations on the WoS at the time of writing. Barr et al. (2013) recommended maximal linear mixed-effects models (LMEMs) as the "gold standard" in psycholinguistics, to determine the maximal random effects structure as the best option for mixed model analysis. However, with the most recent and strongest citation burst starting in 2016, Bates (2015) provided the lme4 package for mixed model analysis and argued that the application of maximally randomized structures may not be an appropriate strategy because overly complex random effects structures are prone to becoming uninterpretable. It is to be noted that this is a highly cited reference, with 9,675 citations at the time of writing.

Some of cited references with more recent citation bursts revolve around datasets for the collection and evaluation of continuous variables, variance, and computational models of word recognition in psycholinguistic research. References by Keuleers (Keuleers et al., 2010, 2012) ranked the third and fourth strongest citation bursts, respectively, starting in 2015. Keuleers et al. (2010) presented a database of behavioral word-processing data for Dutch mono- and di-syllabic words and nonwords, namely the Dutch Lexicon Project (DLP), for mixed effect analyses and mathematical modeling of psychological data. Subsequently, in analogy with previous databases, the British Lexicon Project (BLP) (Keuleers et al., 2012) filled the vacancy between the English Lexicon

Project (ELP) and the DLP, given that the repeated measures design of DLP was applied to the English language in this database. Van Heuven et al. (2014) presented an improved version of a word frequency database, SUBTLEX-UK, for a more stringent evaluative and comparative study of the word frequency effect. This study, with the most recent citation burst (since 2016), presents subbased British word frequency norms to address the limitations when the word must be selected based on frequency information. Interestingly, in previous sections, the English Lexicon Project (ELP) (Balota et al., 2007) has been computed as one of the highly cited references in both cluster #3 and even the whole co-citation network. However, the absence of this study in the listing of references with recent citation bursts, as shown in Table 13, seems to imply that ELP might be gradually falling out of favor by researchers. According to Keuleers et al. (2012), one of the possible reasons could be the fact that a growing number of researchers have been aware of the distinction among different datasets. Specifically, ELP differs from other databases concerning their language (e.g., English vs. Dutch), spelling (American word usage vs. British word usage), stimuli presentation, and type of nonwords used. Thus, it becomes impossible to compare results given by studies using different databases.

In summary, these more recent and impactful references, based on their citation bursts, show ample evidence for the influences of top-down processing in VWR with more profound considerations. Moreover, an accumulating effect in creating and analyzing datasets of behavioral trial-level data is of wide-reaching and significant concern within the research community.

4 Discussion and conclusion

In this study, we presented an analysis of the co-citation network in the VWR field using CiteSpace, a popular method in bibliometrics. This approach is introduced to a nonspecialized audience through a step-by-step description of the network visualization and parameters used for its analysis. The analysis carried out in this study enables tracking of the dynamics of the VWR research frontier over the last decade and explore emerging trends and fundamental and breakthrough contributions by reviewing highly impactful references, as shown by parameters such as BC or citation burst. Taken together, this quantitative bibliometric analysis provides insights from the consistent findings, coming mostly from alphabetic languages, regarding theoretical accounts of "what" types of representations are stored for a printed word in the linguistic system, "where" they are activated (i.e., their neural generators), "when" they interact during the processing, and "how" they are assembled to be recognized as a whole word.

(1) "*What*": cluster #0 with the largest size has shown that orthographic information plays a significant role in recognition processing. A fundamental issue that must be addressed in any computational model of VWR is how the position of letters within a word is encoded because, without letter position coding, readers remain unaware when *aliments* are substituted by *ailments* or even *garden* by *danger*. Moreover, phonological information exerts important influences on initial orthographic form-based words, given the evidence from word-reading studies. Several behavioral studies have revealed that morphemes, as independent linguistic units, play an important role in the early stages of word recognition. However, the activation of morpho-semantics during the processing of morphologically complex words remains controversial. Furthermore, there is considerable evidence that words associated with relatively more semantic information can be recognized faster across different lexical processing tasks, showing a fundamental role of semantics in VWR.

(2) "*Where*" and "*when*": neural accounts of VWR emerged with the availability of techniques that have shown that phonological and semantic information modulates early processing of

printed words. Studies advocating top-down processing have strengthened their position in the landscape of VWR over the past decade, although there have been heated debates regarding the precise cortical location and timing of access to these representations during processing. In this view, the interactivity between top-down and bottom-up is likely to dominate the near future of the VWR domain.

(3) "*How*": the architecture of the VWR system has been a longstanding debate in cognitive science, focusing on how orthographic representation and higher-level linguistic representations operate in the initial form-based processing of a printed (or written) word. Reviewing the recent wave of studies, evidenced by references with most recent citation bursts, has allowed the identification of emerging trends and patterns in the development of the VWR research and the generation of VWR models. Specifically, the processing of orthographic information in recognition systems, such as letter position coding, is the product of a cross-linguistic environment rather than the surface structure of letter sequences. Hence, ongoing form-level processing of a printed word cannot be explained or understood without considering the overall structure that allows for phonological, morphological, and semantic information observed in early orthographic processing. Therefore, these directions emerging from the abovementioned claims allocate a top-down influence on the processing of printed information.

Apart from "what," "when," "where," and "how" questions, various databases and methods have been developed to help researchers conduct mixed effect analyses and mathematical modeling of psychological data. Concerning the option for mixed model analysis, disputes arise as to whether the maximally random effects structures are appropriate for interpreting mixed effects (Barr et al., 2013; Bates et al., 2015). Moreover, compared to the English Lexicon Project (Balota et al., 2007), a highly cited reference in both cluster #3 and the co-citation network, the Dutch Lexicon Project, and the British Lexicon Project presented by Keuleers (Keuleers et al., 2010, 2012) are more popular in terms of their recent citation bursts. These databases offer researchers a new dataset for mixed effects analyses and mathematical models in terms of their recent citation bursts.

The present bibliometrics-based review shows a growing interest over the period between 2009 and 2018, considering the linguistic system as an interactive network in which different processes operate in parallel and in both top-down and bottom-up manner. Nonetheless, the major trends are affected by the methods and algorithms implemented in the CiteSpace, and hence the presented results should be further examined in future studies. Furthermore, none of these trends have emerged in the past 10 years, affirming that the recognition system is fully interactive and processed in a top-down manner in which higher-level linguistic information modulates early perceptual orthographic structure, and more trends are expected to emerge from other opposing views in the future. Indeed, it is not easy to resolve the contrasting issue about whether different types of representations interact at all processing stages in the context of the sound-based script such as alphabetic systems, given its systematic mapping between perceptual orthographic forms and linguistic information is blurred. One recommendation is to conduct research by using experimental stimuli in logographic languages (e.g., Chinese), which would allow for the investigation of the demarcation between top-down and bottom-up processing in VWR, given its relatively arbitrary mapping between orthographic and other linguistic information. Therefore, there is still a long way to go before we can set universal principles for studying, monitoring, understanding, and eventually modeling the processing of a printed word.

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References

Abbasi, A., Hossain, L., & Leydesdorff, L. (2012). Betweenness centrality as a driver of preferential attachment in the evolution of research collaboration networks. *Journal of Informetrics*, *6*(1), 403–412. https://doi.org/10.1016/j.joi.2012.01.002

Alvarez, C., Carreiras, M., & Perea, M. (2004). Are syllables phonological units in visual word recognition? *Language and Cognitive Processes*, *19*(3), 427–452. https://doi.org/10.1080/01690960344000242

Andrews, S., & Lo, S. (2013). Is morphological priming stronger for transparent than opaque words? It depends on individual differences in spelling and vocabulary. *Journal of Memory and Language*, *68*(3), 279–296. https://doi.org/10.1016/j.jml.2012.12.001

Aschenbrenner, A. J., Balota, D. A., Weigand, A. J., Scaltritti, M., & Besner, D. (2017). The first letter position effect in visual word recognition: The role of spatial attention. *Journal of Experimental Psychology-Human Perception and Performance*, *43*(4), 700–718. https://doi.org/10.1037/xhp0000342

Baayen, R. H., Davidson, D. J., & Bates, D. M. (2008). Mixed-effects modeling with crossed random effects for subjects and items. *Journal of Memory and Language*, *59*(4), 390–412. https://doi.org/10.1016/j.jml.2007.12.005

Baayen, R. H., Milin, P., Durdevic, D. F., Hendrix, P., & Marelli, M. (2011). An amorphous model for morphological processing in visual comprehension based on naive discriminative learning. *Psychological Review*, *118*(3), 438–481. https://doi.org/10.1037/a0023851

Balota, D. A., Cortese, M. J., Sergent-Marshall, S. D., Spieler, D. H., & Yapp, M. J. (2004). Visual word recognition for single-syllable words. *Journal of Experimental Psychology: General*, *133*, 283–316.

Balota, D. A., Yap, M. J., Cortese, M. J., Hutchison, K. A., Kessler, B., Loftis, B., Neely, J. H., Nelson, D. L., Simpson, G. B., & Treiman, R. (2007). The English Lexicon Project. *Behavior Research Methods*, *39*(3), 445–459. https://doi.org/10.3758/bf03193014

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*(3), 255–278. https://doi.org/10.1016/j.jml.2012.11.001

Bates, D., Maechler, M., Bolker, B. M., & Walker, S. C. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.1007/0-387-22747-4_4

Beyersmann, E., Castles, A., & Coltheart, M. (2012). Morphological processing during visual word recognition in developing readers: Evidence from masked priming. *Quarterly Journal of Experimental Psychology*, *65*(7), 1306–1326. https://doi.org/10.1080/17470218.2012.656661

Beyersmann, E., Ziegler, J. C., Castles, A., Coltheart, M., Kezilas, Y., & Grainger, J. (2016). Morpho-orthographic segmentation without semantics. *Psychonomic Bulletin & Review*, *23*(2), 533–539. https://doi.org/10.3758/s13423–015–0927-z

Bosse, M.-L., Tainturier, M. J., & Valdois, S. (2007). Developmental dyslexia: The visual attention span deficit hypothesis. *Cognition*, *104*(2), 198–230. https://doi.org/10.1016/j.cognition.2006.05.009

Brysbaert, M., & New, B. (2009). Moving beyond Kucera and Francis: A critical evaluation of current word frequency norms and the introduction of a new and improved word frequency measure for American English. *Behavior Research Methods*, *41*(4), 977–990. https://doi.org/10.3758/brm.41.4.977

Buchanan, L., Westbury, C., & Burgess, C. (2001). Characterizing semantic space: Neighborhood effects in word recognition. *Psychonomic Bulletin & Review*, *8*(3), 531–544. https://doi.org/10.3758/bf03196189

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*(2), 90–98. https://doi.org/10.1016/j.tics.2013.11.005

Carreiras, M., Ferrand, L., Grainger, J., & Perea, M. (2005). Sequential effects of phonological priming in visual word recognition. *Psychological Science*, *16*(8), 585–589. https://doi.org/10.1111/j.1467–9280.2005.01579.x

Chauncey, K., Holcomb, P. J., & Grainger, J. (2008). Effects of stimulus font and size on masked repetition priming: An event-related potentials (ERP) investigation. *Language and Cognitive Processes*, *23*(1), 183–200. https://doi.org/10.1080/01690960701579839

Chen, C. (2006). CiteSpace II: Detecting and visualizing emerging trends and transient patterns in scientific literature. *Journal of the American Society for Information Science and Technology*, *57*(3), 359–377. https://doi.org/10.1002/asi.20317

Chen, C. (2012). Emerging trends in regenerative medicine: A scientometric analysis in CiteSpace. *Expert Opinions on Biological Therapy*, *12*(5), 593–608. https://doi.org/10.1517/14712598.2012.674507

Chen, C. (2014a) *The CiteSpace Manual*. http://cluster.ischool.drexel.edu/~cchen/citespace/CiteSpaceManual.pdf

Chen, C. (2016). *CiteSpace: A Practical Guide for Mapping Scientific Literature*. Nova Science.

Chen, C. (2017). Science mapping: A systematic review of the literature. *Journal of Data and Information Science*, *2*(2), 1–40. https://doi.org/10.1515/jdis-2017–0006

Chen, C., Chen, Y., Horowitz, M., Hou, H., Liu, Z., & Pellegrino, D. (2009). Towards an explanatory and computational theory of scientific discovery. *Journal of Informetrics*, *3*(3), 191–209. https://doi.org/10.1016/j.joi.2009.03.004

Chen, C., Dubin, R., & Kim, M. C. (2014b). Emerging trends and new developments in regenerative medicine: A scientometric update (2000–2014). *Expert Opinion on Biological Therapy*, *14*(9), 1295–1317. https://doi.org/10.1517/14712598.2014.920813

Chen, C., Dubin, R., & Kim, M. C. (2014c). Orphan drugs and rare diseases: A scientometric review (2000–2014). *Expert Opinion on Orphan Drugs*, *2*(7), 709–724. https://doi.org/10.1517/21678707.2014.920251

Chen, C., Hu, Z., Liu, S., & Tseng, H. (2012). Emerging trends in regenerative medicine: A scientometric analysis in CiteSpace. *Expert Opinion on Biological Therapy*, *12*, 593–608. https://doi.org/10.1517/14712598.2012.674507

Chen, C., Ibekwe-SanJuan, F., & Hou, J. (2010). The structure and dynamics of cocitation clusters: A multiple-perspective cocitation analysis. *Journal of the American Society for Information Science and Technology*, *61*(7), 1386–1409. https://doi.org/10.1002/asi.21309

Chen, C., & Song, M. (2019). Visualizing a field of research: A methodology of systematic scientometric reviews. *PLoS ONE 14*(10): e0223994. https://doi.org/10.1371/journal.pone.0223994

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*(1), 204–256. https://doi.org/10.1037//0033295x.108.1.204

Conrad, M., Carreiras, M., Tamm, S., & Jacobs, A. M. (2009). Syllables and bigrams: Orthographic redundancy and syllabic units affect visual word recognition at different processing levels. *Journal of Experimental Psychology-Human Perception and Performance*, *35*(2), 461–479. https://doi.org/10.1037/a0013480

Cop, U., Keuleers, E., Drieghe, D., & Duyck, W. (2015). Frequency effects in monolingual and bilingual natural reading. *Psychonomic Bulletin & Review*, *22*(5), 1216–1234. https://doi.org/10.3758/s13423–015–0819–2

Cortese, M. J., & Fugett, A. (2004). Imageability ratings for 3,000 monosyllabic words. *Behavior Research Methods Instruments & Computers*, *36*(3), 384–387. https://doi.org/10.3758/bf03195585

Cortese, M. J., & Khanna, M. M. (2007). Age of acquisition predicts naming and lexical-decision performance above and beyond 22 other predictor variables: An analysis of 2,342 words. *The Quarterly Journal of Experimental Psychology*, *60*, 1072–1082.

Cortese, M. J., & Schock, J. (2013). Imageability and age of acquisition effects in disyllabic word recognition. *The Quarterly Journal of Experimental Psychology*, *66*, 946–972.
Davis, C. J. (2010). The spatial coding model of visual word identification. *Psychological Review*, *117*(3), 713–758. https://doi.org/10.1037/a0019738
Dehaene, S., & Cohen, L. (2011). The unique role of the visual word form area in reading. *Trends in Cognitive Sciences*, *15*(6), 254–262. https://doi.org/10.1016/j.tics.2011.04.003
Dehaene, S., Cohen, L., Morais, J., & Kolinsky, R. (2015). Illiterate to literate: Behavioural and cerebral changes induced by reading acquisition. *Nature Reviews Neuroscience*, *16*(4), 234–244. https://doi.org/10.1038/nrn3924
Dunabeitia, J. A., Aviles, A., & Carreiras, M. (2008). NoA's ark: Influence of the number of associates in visual word recognition. *Psychonomic Bulletin & Review*, *15*(6), 1072–1077. https://doi.org/10.3758/pbr.15.6.1072
Feldman, L. B., Connor, P., & Moscosco del Prado Martin, F. (2009). Early morphological processing is morphosemantic and not simply morpho-orthographic: A violation of form-then-meaning accounts of word recognition. *Psychonomic Bulletin & Review*, *16*(4), 684–691. https://doi.org/10.3758/pbr.16.4.684
Flinker, A., Korzeniewska, A., Shestyuk, A. Y., Franaszczuk, P. J., Dronkers, N. F., Knight, R. T., & Crone, N. E. (2015). Redefining the role of Broca's area in speech. *Proceedings of the National Academy of Sciences*, *112*(9), 2871–2875. https://doi.org/10.1073/pnas.1414491112
Forster, K. I. (2004). Category size effects revisited: Frequency and masked priming effects in semantic categorization. *Brain and Language*, *90*(1–3), 276–286. https://doi.org/10.1016/s0093–934x(03)00440–1
Hauk, O., Davis, M. H., Ford, M., Pulvermüller, F., & Marslen-Wilson, W. D. (2006). The time course of visual word recognition as revealed by linear regression analysis of ERP data. *NeuroImage*, *30*(4), 1383–1400. https://doi.org/10.1016/j.neuroimage.2005.11.048
Gerrig, R. (1986). Processes and products of lexical access. *Language and Cognitive Processes*, *1*, 187–196.
Gomez, P., Ratcliff, R., & Perea, M. (2008). The overlap model: A model of letter position coding. *Psychological Review*, *115*(3), 577–601. https://doi.org/10.1037/a0012667
Grainger, J. (2008). Cracking the orthographic code: An introduction. *Language and Cognitive Processes*, *23*(1), 1–35. https://doi.org/10.1080/01690960701578013
Grainger, J., Bertrand, D., Lete, B., Beyersmann, E., & Ziegler, J. C. (2016a). A developmental investigation of the first-letter advantage. *Journal of Experimental Child Psychology*, *152*, 161–172. https://doi.org/10.1016/j.jecp.2016.07.016
Grainger, J., Dufau, S., & Ziegler, J. C. (2016b). A vision of reading. *Trends in Cognitive Sciences*, *20*(3), 171–179. https://doi.org/10.1016/j.tics.2015.12.008
Grainger, J., & Holcomb, P. J. (2009). Watching the word go by: On the time-course of component processes in visual word recognition. *Language and Linguistics Compass*, *3*(1), 128–156. https://doi.org/10.1002/asi.21309
Grainger, J., Lete, B., Bertrand, D., Dufau, S., & Ziegler, J. C. (2012). Evidence for multiple routes in learning to read. *Cognition*, *123*(2), 280–292. https://doi.org/10.1016/j.cognition.2012.01.003
Grainger, J., & Van Heuven, W. J. B. (2004). Modeling letter position coding in printed word perception. *Bonin P the Mental Lexicon*, (19), 1–23. https://doi.org/10.1080/01690960344000198
Grainger, J., & Ziegler, J. C. (2011). A dual-route approach to orthographic processing. *Frontiers in Psychology*, *2*. https://doi.org/10.3389/fpsyg.2011.00054
Holcomb, P. J., & Grainger, J. (2006). On the time course of visual word recognition: An event-related potential investigation using masked repetition priming. *Journal of Cognitive Neuroscience*, *18*(10), 1631–1643. https://doi.org/10.1162/jocn.2006.18.10.1631
Indefrey, P. (2011). The spatial and temporal signatures of word production components: a critical update. *Frontiers in Psychology*, *2*. https://doi.org/10.3389/fpsyg.2011.00255
Johnson-Laird, P. N. (1975). Meaning and the mental lexicon. In A. Kennedy & A. Wilkes (Eds.), *Studies in long-term memory* (pp. 123–142). John Wiley.
Keuleers, E., Diependaele, K., & Brysbaert, M. (2010). Practice effects in large-scale visual word recognition studies: A lexical decision study on 14,000 Dutch mono- and disyllabic words and nonwords. *Frontiers in Psychology*, *1*. https://doi.org/10.3389/fpsyg.2010.00174

Keuleers, E., Lacey, P., Rastle, K., & Brysbaert, M. (2012). The British Lexicon Project: Lexical decision data for 28,730 monosyllabic and disyllabic English words. *Behavior Research Methods*, *44*(1), 287–304. https://doi.org/10.3758/s13428–011–0118–4

Kleinberg, J. (2003). Bursty and hierarchical structure in streams. *Data Mining and Knowledge Discovery*, *7*(4), 373–397. https://doi.org/10.1023/A:1024940629314

Kutas, M., & Federmeier, K. D. (2011). Thirty years and counting: Finding meaning in the N400 component of the Event-Related Brain Potential (ERP). In S. T. Fiske, D. L. Schacter, & S. E. Taylor (Eds.), *Annual Review of Psychology* (vol. 62, pp. 621–647). Annual Review Inc. https://doi.org/10.1146/annurev.psych.093008.131123

Laszlo, S., & Federmeier, K. D. (2011). The N400 as a snapshot of interactive processing: Evidence from regression analyses of orthographic neighbor and lexical associate effects. *Psychophysiology*, *48*(2), 176–186. https://doi.org/10.1111/j.1469–8986.2010.01058.x

Lerma-Usabiaga, G., Carreiras, M., & Paz-Alonso, P. M. (2018) Converging evidence for functional and structural segregation within the left ventral occipitotemporal cortex in reading. *Proceedings of the National Academy of Sciences*, *115*(42). https://doi.org/10.1073/pnas.1803003115.

Liberman, A. M., Cooper, F. S., Shankweiler, D. P., & Studdert-Kennedy, M. (1967). Perception of the speech code. *Psychological Review*, *74*, 431–461.

Li, J., & Chen, C. (2016). *CiteSpace: Text mining and visualization in scientific literature*. Capital University of Economics and Business Press.

Li, Y., Xu, Z., Wang, X., & Filip, F. G. (2019). Studies in informatics and control: A bibliometric analysis from 2008 to 2019. *International Journal of Computers Communications & Control*, *14*, 633–652. https://doi.org/10.15837/ijccc.2019.6.3753

Li, X. Y., Yuan, J. H., Shi, Y., Sun, Z. L., & Ruan, J. H. (2020). Emerging Trends and innovation modes of internet finance-results from co-word and co-citation networks. *Future Internet*, *12*(3), 14. https://doi.org/10.3390/fi12030052

Maloney, E., Risko, E. F., O'Malley, S., & Besner, D. (2009). Tracking the transition from sublexical to lexical processing: On the creation of orthographic and phonological lexical representations. *The Quarterly Journal of Experimental Psychology*, *62*, 858–867.

Martin, A., Schurz, M., Kronbichler, M., & Richlan, F. (2015). Reading in the brain of children and adults: A meta-analysis of 40 functional magnetic resonance imaging studies. *Human Brain Mapping*, *36*(5), 1963–1981. https://doi.org/10.1002/hbm.22749

Norris, D., Kinoshita, S., & van Casteren, M. (2010). A stimulus sampling theory of letter identity and order. *Journal of Memory and Language*, *62*(3), 254–271. https://doi.org/10.1016/j.jml.2009.11.002

Perea, M., & Lupker, S. J. (2004). Can CANISO activate CASINO? Transposed-letter similarity effects with nonadjacent letter positions. *Journal of Memory and Language*, *51*(2), 231–246. https://doi.org/10.1016/j.jml.2004.05.005

Perry, C., Ziegler, J. C., & Zorzi, M. (2007). Nested incremental modeling in the development of computational theories: The CDP+ model of reading aloud. *Psychological Review*, *114*(2), 273–315. https://doi.org/10.1037/0033295x.114.2.273

Perry, C., Ziegler, J. C., & Zorzi, M. (2010). Beyond single syllables: Large-scale modeling of reading aloud with the Connectionist Dual Process (CDP++) model. *Cognitive Psychology*, *61*(2), 106–151. https://doi.org/10.1016/j.cogp-sych.2010.04.001

Pexman, P. M., Hargreaves, I. S., Siakaluk, P. D., Bodner, G. E., & Pope, J. (2008). There are many ways to be rich: Effects of three measures of semantic richness on visual word recognition. *Psychonomic Bulletin & Review*, *15*(1), 161–167. https://doi.org/10.3758/pbr.15.1.161

Pexman, P. M., Holyk, G. G., & Monfils, M. H. (2003). Number-of-features effects and semantic processing. *Memory & Cognition*, *31*(6), 842–855. https://doi.org/10.3758/bf03196439

Pexman, P. M., Lupker, S. J., & Hino, Y. (2002). The impact of feedback semantics in visual word recognition: Number-of-features effects in lexical decision and naming tasks. *Psychonomic Bulletin & Review*, *9*(3), 542–549. https://doi.org/10.3758/bf03196311

Pickering, M. J., & Gambi, C. (2018). Predicting while comprehending language: A theory and review. *Psychological Bulletin*, *144*(10). https://doi.org/10.1037/bul0000158

Price, C. J. (2012). A review and synthesis of the first 20 years of PET and fMRI studies of heard speech, spoken language and reading. *Neuroimage*, *62*(2), 816–847. https://doi.org/10.1016/j.neuroimage.2012.04.062

Price, C. J., & Devlin, J. T. (2011). The interactive account of ventral occipitotemporal contributions to reading. *Trends in Cognitive Sciences*, *15*(6), 246–253. https://doi.org/10.1016/j.tics.2011.04.001

Ramus, F., Marshall, C. R., Rosen, S., & van der Lely, H. K. J. (2013). Phonological deficits in specific language impairment and developmental dyslexia: Towards a multidimensional model. *Brain*, *136*(2), 630–645. https://doi.org/10.1093/brain/aws356

Rastle, K., & Brysbaert, M. (2006). Masked phonological priming effects in English: Are they real? Do they matter? *Cognitive Psychology*, *53*(2), 97–145. https://doi.org/10.1016/j.cogpsych.2006.01.002

Rastle, K., Davis, M. H., Marslen-Wilson, W. D., & Tyler, L. K. (2000). Morphological and semantic effects in visual word recognition: A time-course study. *Language and Cognitive Processes*, *15*(4–5), 507–537. https://doi.org/10.1080/01690960050119689

Rastle, K., & Davis, M. H. (2008). Morphological decomposition based on the analysis of orthography. *Language and Cognitive Processes*, *23*(7–8), 942–971. https://doi.org/10.1080/01690960802069730

Rastle, K., Davis, M. H., & New, B. (2004). The broth in my brother's brothel: Morpho-orthographic segmentation in visual word recognition. *Psychonomic Bulletin & Review*, *11*(6), 1090–1098. https://doi.org/10.3758/bf03196742

Schierz, P. G., Schilke, O., & Wirtz, B. W. (2010). Understanding consumer acceptance of mobile payment services: An empirical analysis. *Electronic Commerce Research and Applications*, *9*(3), 209–216. https://doi.org/10.1016/j.elerap.2009.07.005

Schoonbaert, S., & Grainger, J. (2004). Letter position coding in printed word perception: Effects of repeated and transposed letters. *Language and Cognitive Processes*, *19*(3), 333–367. https://doi.org/10.1080/01690960344000198

Share, D. L. (2008). On the anglocentricities of current reading research and practice: The perils of overreliance on an "Outlier" orthography. *Psychological Bulletin*, *134*(4), 584–615. https://doi.org/10.1037/00332909.134.4.584

Siakaluk, P. D., Pexman, P. M., Aguilera, L., Owen, W. J., & Sears, C. R. (2008). Evidence for the activation of sensorimotor information during visual word recognition: The body-object interaction effect. *Cognition*, *106*(1), 433–443. https://doi.org/10.1016/j.cognition.2006.12.011

Small, H. (1973). Co-citation in the scientific literature: A new measure of the relationship between two documents. *Journal of the American Society for Information Science*, *24*, 265–269. https://doi.org/10.1002/asi.4630240406

Sun, J. F., Zhou, Z. C., Huang, J., & Li, G. X. (2020). A bibliometric analysis of the impacts of air pollution on children. *International Journal of Environmental Research and Public Health*, *17*(4), 1277. https://doi.org/10.3390/ijerph17041277

Taylor, J. S. H., Rastle, K., & Davis, M. H. (2013). Can cognitive models explain brain activation during word and pseudoword reading? A meta-analysis of 36 neuroimaging studies. *Psychological Bulletin*, *139*(4), 766–791. https://doi.org/10.1037/a0030266

Trevor, A. H. (2014). The psychology of language: From data to theory (4th ed). Psychology Press.

van Heuven, W. J. B., Mandera, P., Keuleers, E., & Brysbaert, M. (2014). SUBTLEX-UK: A new and improved word frequency database for British English. *Quarterly Journal of Experimental Psychology*, *67*(6), 1176–1190. https://doi.org/10.1080/17470218.2013.850521

Vidyasagar, T. R., & Pammer, K. (2010). Dyslexia: A deficit in visuo-spatial attention, not in phonological processing. *Trends in Cognitive Sciences*, *14*(2), 57–63. https://doi.org/10.1016/j.tics.2009.12.003

Vinckier, F., Dehaene, S., Jobert, A., Dubus, J. P., Sigman, M., & Cohen, L. (2007). Hierarchical coding of letter strings in the ventral stream: Dissecting the inner organization of the visual word-form system. *Neuron*, *55*(1), 143–156. https://doi.org/10.1016/j.neuron.2007.05.031

Wang, H., Yan, X., & Guo, H. (2018). Visualizing the knowledge domain of embodied language cognition: A bibliometric review. *Digital Scholarship in the Humanities*. https://doi.org/10.1093/llc/fqy010

Wheat, K. L., Cornelissen, P. L., Frost, S. J., & Hansen, P. C. (2010). During visual word recognition, phonology is accessed within 100 ms and may be mediated by a speech production code: Evidence from

magnetoencephalography. *Journal of Neuroscience*, *30*(15), 5229–5233. https://doi.org/10.1523/jneurosci.444809.2010
Woollams, A. M., Ralph, M. A. L., Madrid, G., & Patterson, K. E. (2016). Do you read how I read? Systematic individual differences in semantic reliance amongst normal readers. *Frontiers in Psychology, 7*. https://doi.org/10.3389/fpsyg.2016.01757
Wu, M., Wang, Y., Yan, C., & Zhao, Y. (2020). Study on subclinical hypothyroidism in pregnancy: A bibliometric analysis via CiteSpace. *The Journal of Maternal-Fetal & Neonatal Medicine*, 1–12. https://doi.org/10.1080/14767058.2020.1729731
Xu, Z., & Yu, D. (2019). A bibliometrics analysis on big data research (2009–2018). *Journal of Data, Information and Management*, *1*(1), 3–15. https://doi.org/10.1007/s42488–019–00001–2
Yap, M. J., & Balota, D. A. (2009). Visual word recognition of multisyllabic words. *Journal of Memory and Language*, *60*(4), 502–529. https://doi.org/10.1016/j.jml.2009.02.001
Yap, M. J., Lim, G. Y., & Pexman, P. M. (2015). Semantic richness effects in lexical decision: The role of feedback. *Memory & Cognition*, *43*(8), 1148–1167. https://doi.org/10.3758/s13421–015–0536–0
Yap, M. J., Pexman, P. M., Wellsby, M., Hargreaves, I. S., & Huff, M. J. (2012). An abundance of riches: Cross-task comparisons of semantic richness effects in visual word recognition. *Frontiers in Human Neuroscience*, *6*. https://doi.org/10.3389/fnhum.2012.00072
Yap, M. J., Tan, S. E., Pexman, P. M., & Hargreaves, I. S. (2011). Is more always better? Effects of semantic richness on lexical decision, speeded pronunciation, and semantic classification. *Psychonomic Bulletin & Review*, *18*(4), 742–750. https://doi.org/10.3758/s13423–011–0092-y
Yarkoni, T., Balota, D., & Yap, M. (2008). Moving beyond Coltheart's N: A new measure of orthographic similarity. *Psychonomic Bulletin & Review*, *15*(5), 971–979. https://doi.org/10.3738/pbr.15.5.971
Yu, D., Xu, Z., Kao, Y., & Lin, C. (2018). The structure and citation landscape of IEEE transactions on fuzzy systems (1994–2015). *IEEE Transactions on Fuzzy Systems*, *26*(2), 430–442. https://doi.org/10.1109/TFUZZ.2017.2672732
Yu, D., Xu, Z., Pedrycz, W., & Wang, W. (2017). Information sciences 1968–2016: A retrospective analysis with text mining and bibliometric. *Information Sciences, 418–419*, 619–634. https://doi.org/10.1016/j.ins.2017.08.031
Zhu, J., & Hua, W. (2017). Visualizing the knowledge domain of sustainable development research between 1987 and 2015: A bibliometric analysis. *Scientometrics*, *110*(2), 893–914. https://doi.org/10.1007/s11192–016–2187–8
Ziegler, J. C., & Goswami, U. (2005). Reading acquisition, developmental dyslexia, and skilled reading across languages: A psycholinguistic grain size theory. *Psychological Bulletin*, *131*(1), 3–29. https://doi.org/10.1037/00332909.131.1.3
Ziegler, J. C., Perry, C., Jacobs, A. M., & Braun, M. (2001). Identical words are read differently in different languages. *Psychological Science*, *12*(5), 379–384. https://doi.org/10.1111/14679280.00370