Reading Patterns: Statistical Learning Mechanisms in Skilled Reading

Supervisor:
Prof. Davide Crepaldi

Candidate:
Mara De Rosa

Thesis submitted for the degree of Doctor of Philosophy in
Cognitive Neuroscience

International School for Advanced Studies
Trieste, March 2022

To Alpha Canis Majoris

Contents

List of Figures

List of Tables

Acknowledgements

I am deeply thankful to my supervisor Dr. Davide Crepaldi for his support, his patience, for his honest enthusiasm and his enthusiastic honesty. Davide has always kept a keen eye on the development of what he calls “my personal toolbox”, ensuring that I had the right challenges to grow, both on a technical and a personal level. I appreciate above all his kind way of encouraging me to quench my curiosity and pursue my interests, guiding me without ever depriving me of independence.

I am beyond honored to have Dr. Domenica Bueti, Dr. Ram Frost, Dr. Manuel Perea and Dr. Alessandro Treves as members of my examination committee, as I look forward to their insights on the research included in this thesis. The works reported herein also include the results of collaborations that involved the precious contributions of Dr. Roberto Bottini, Dr. Yamil Vidal and Dr. Lorenzo Vignali, along with the assistance of Marjina Bellida, Anna D’Urso and Mattia Sambo. I am profoundly thankful for all of their inputs, and for the roles each of them played in this journey.

A special mention goes to my closest collaborator, the kind, passionate, brilliant, humble Dr. Maria Ktori. My words fail to give justice to our bond, forged by endless brainstorming sessions and phone calls, chats, opinion exchanges, questions, advice, doubts, laughter and tears. My work and my life would not have been the same without Maria, or, as I always refer to her, the other – the better – half of my brain.

I am thankful for the kaleidoscope of experiences so prepotently impressed in my mind, each of which has contributed to shape the person writing these lines. The long and deep conversations around language, morphology and statistical learning, featuring the incredible minds of Jon Carr, Romain Brasselet and Jana Hasenäcker. The inspiring dedication of Domenica Bueti and Matteo Bertolini within the Student-Professor Joint Committee, and the positive impact we achieved together. The reassuring smile of Marijana Sjekloća, the shelter (both metaphorical and literal) full of laughter and support I have always found by the amazing Valentina Pescuma, Francesca Franzon and Dunia Giomo. The respect and passion of Antonella Torrisi, a pure soul and an endless source of inspiration. The countless hours on the Rive with Andrea Papale, and those laughing with Sara De Carlo. The unique attitude Giorgia Zoccolan has towards all things in life, for which her friendship is an evergreen source of wisdom, amusement and comfort. All of these experiences were uniquely colored by the presence of my pillars, Jasmine Pani, Matteo Zampieri and Gianfranco Fortunato: we walked miles together, and I wouldn't have had it any other way.

Finally, thanks to Diego Doimo for reappearing after nine years bringing tales of hope – that is, for trusting me with a new cactus despite the fact that I managed to kill the first one. Thanks to my generous brother, my contemplative father and my invincible mother, for what can only be described as the purest expression of unconditional love and patience.

«There's a science to walking through windows without you».

Abstract

The research included in the present thesis investigates how statistical learning mechanisms relate to the early stages of visual word recognition in skilled reading. Particularly, we ask whether the lifelong experience with textual regularities can provide a source of information for readers to exploit, and whether it can account for some of the fundamental skilled reading phenomena reported in the literature. Chapter 2 assesses the role of letter chunk frequency in morpho-orthographic processing, by comparing suffixes to highly frequent word endings in a masked priming lexical decision study. Chapter 3 includes this comparison as part of a hierarchy of contrasts, each of which tackles a linguistic feature potentially relevant for skilled reading. Selective discrimination responses are here captured through the adoption of the Fast Periodic Visual Stimulation paradigm (FPVS), coupled with MEG recordings. The FPVS technique also features the study described in Chapter 4, which reveals how the hidden regularities exhibited by a visual stream can inform the emergence of neural discrimination responses in skilled readers. Chapter 5 includes three experiments investigating whether the letter co-occurrence regularities inherent in the language can aid letter processing within briefly presented strings of consonants. Cumulatively, the evidence collected suggests that the knowledge of the statistical regularities that characterize the written input supports early orthographic processes in skilled reading.

Chapter 1

General Introduction

For skilled readers, the processing of written input unfolds rapidly and effortlessly. It is a precisely calibrated integration of processes, uniquely mastered by the human brain, that allows it to efficiently handle texts that range from items on a shopping list to Shakespeare's sonnets. Even reading these lines is extremely natural: each written word is swiftly identified with remarkable accuracy, and meaning unravels while the reader's eyes glide over the text.

Such a seemingly simple, natural skill is rather remarkable. Compared to spoken words, which develop over time, under typical reading conditions the visual information associated with printed words is immediately available to the reader, and remains stable over time. Within a few hundred milliseconds, skilled readers can access their knowledge of pronunciation and meaning – they can, in a nutshell, read. For this to happen, strings of letters need to be recognized as known word units. Visual word identification is indeed paramount in reading, and understanding the mechanisms and building blocks that underpin it has been in the limelight of cognitive science for over a century (Huey, 1908).

Together with offering a model system in cognitive psychology, serving as test bench for theoretical constructs like serial search (Forster & Davis, 1984) or rule-based computations (Coltheart, 1978), visual word recognition is still a tantalizing phenomenon in its own right. Behavioral and neuroimaging data, alongside with theoretical and computational models, attest the long history of attempts and efforts in trying to address the interplay of visual and linguistic factors at the basis of the processing of written words. A unified understanding of such early stages of reading is however still far from grasp: what are the relevant units taken into consideration by the reading brain? And how are they assembled to achieve recognition? What are the neural bases of such process(es), and to what extent can they be considered language-specific? The work herein described attempts to shed some light on some of these open questions by assessing the role of written regularities in skilled reading.

1.2 Part-based and Holistic Processes in Visual Word Identification

Early accounts of visual word identification focused on whether printed words are recognized holistically or through their constituents (i.e., letters), a fundamental question connecting literacy with the domain of object recognition (I. Biederman, 1987; Pelli & Tillman, 2007; Treisman & Schmidt, 1982). In the seminal work of Cattell (1886), words appear to transcend the sum of their parts. Tachistoscopic presentations of real words yielded faster and more accurate responses than their anagrams, leading to the idea that words might be recognized on the basis of their visual shapes (such as the pattern that results from a specific combination of letters; Bouma, 1973). Additional evidence in this direction came from letter search experiments showing better performances in reporting individual letters when embedded in a lexical context, as compared to random strings of consonants or even in isolation (Carr et al., 1979; Reicher, 1969; Wheeler, 1970). Taken together, these investigations set forth the so-called *word superiority conundrum* (Grainger & Hannagan, 2014), leading to theorizing words as the minimal processing units in reading.

Word recognition as a holistic process is however extremely inefficient. From a computational point of view, solving shape invariance for individual letters is clearly more efficient than for whole words (Grainger, 2008; Grainger, Dufau, et al., 2012; Grainger & Hannagan, 2014). For the average English reader, recognizing words on the basis of the 26 letters in the alphabet provides a rather parsimonious strategy, if compared to storing and accessing over 30 thousand abstract word-shape representations. Additionally, recognition by word-shape cannot easily accommodate findings indicating that neither case nor font manipulations disrupt the initial stage of letter processing (e.g., Chauncey et al., 2008; Paap et al., 1984), even if visual familiarity affects performance in later stages (e.g., Perea et al., 2015; Perea & Rosa, 2002).

From a perceptual point of view, and as for any other visual object, recognizing words is inevitably affected by perceptual bottlenecks. As masterfully illustrated by Pelli et al. (2003), if individual letters do not reflect enough contrast energy (i.e., the amount of energy needed for distinguishing a known signal from noise), they become too weak to be detected, thus succumbing to squelching and rendering text overall illegible. If filtering out word components makes reading words impossible, it becomes undeniable that words must be identified on the basis of their constituent letters. Nevertheless, this evidence stands in contradiction with the contextual facilitation observed for letters in words.

Several models attempted to reconcile a part-to-whole mapping with word superiority effects. Special consideration has to be given to the Interactive Activation Model (IAM, McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982), that posits three levels of representations, comprising letter-features, letters and visual word forms, linked through facilitatory and inhibitory connections. Visual input activates feature detectors, leading to letter identification; once case and size-invariant, abstract letter identities have been activated, they can map onto compatible lexical representations, which in turn provide top-down feedback along the hierarchy, thus boosting single letter representations. Many notable variants followed (e.g., Coltheart et al., 2001; Grainger & Jacobs, 1994, 1996; Jacobs & Grainger, 1992), extending the scope of the model and increasing its explanatory power towards other reading phenomena, so that nowadays virtually all theories of visual word identification agree on access through constituents.

In the context of a part-to-whole framework, letters are not the only elements that can mediate lexical recognition. From letter features to letters to meaningful letter chunks, fundamental units are indeed identified and exploited to achieve word recognition and, finally, comprehension; understanding the nature and the granularity of such building blocks still poses a major challenge to any unified theory of reading. Following empirical findings encompassing orthographic, phonological and morphological factors, supra-letter, sub-word access units (Taft, 1986) took the form of syllables (Carreiras & Perea, 2002; Spoehr & Smith, 1973), syllabic units (Taft, 1992) and morphemes (Rastle et al., 2004).

A radically different approach is to avoid an explicit definition of intermediate units, a stand taken by distributed connectionist models (e.g., Plaut et al., 1996; Seidenberg, 1987, 2005). Connectionist accounts of reading fueled a fruitful debate on the nature of processes and representations at play in visual word identification (Coltheart, 2006; Rastle & Coltheart, 2006). Critically, these models rely on the idea that orthography-to-meaning, as well as orthography-to-phonology mappings can be discovered through a learning device that capitalizes on the statistical structure of written information. Devoid of explicit representations and rules, complex mappings between input and output layers are mediated by hidden units that allow learning, resulting in a flexible sensitivity to distributional regularities embedded in the language.

1.3 Thriving on Regularities

The notion that skilled readers might strongly rely on statistical regularities is consistent with a more general cognitive ability to extract probabilistic patterns from the input. A large body of phenomena, including but not limited to literacy, demonstrates that the human brain thrives on regularity detection, an aptitude broadly labeled *statistical learning*. Postulated to be at the core of uncertainty reduction (Gibson, 1971) and extraction of relevant information, statistical learning is the ability to capture the distributional properties of the input, generally without awareness and/or overt intention to learn (an aspect that has been extensively discussed, e.g., Perruchet and Pacton, 2006), and constitutes an extremely powerful cognitive resource recruited in information processing (for some recent reviews, see Armstrong et al., 2017; Aslin, 2017; Christiansen, 2019; R. Frost et al., 2019; R. Frost et al., 2015; Thiessen et al., 2013).

In a noisy, overwhelming environment, agents make sense of the overabundant input by looking for consistent associations, co-occurrences and cues, displaying an appetite for regularities that has been observed in a wide variety of experimental settings. A classic illustration comes from Fiser and Aslin (2001), a study involving a set of twelve unfamiliar and highly complex two-dimensional shapes. Participants were passively exposed to a series of visual scenes comprising six of the available items, arranged in strictly controlled three-by-three grids so that elements were consistently presented in pairs, while the probability of each individual element was kept at chance. Without any supervision or feedback, participants familiarized themselves with the hidden regularities in the input, and learned to tease apart elements on the basis of their co-occurrences, thus extrapolating higher-order statistics from the simultaneous display of artificial shapes. Comparable testaments to the brain's tuning to patterns encompass visual (e.g., Fiser & Aslin, 2002), as well as tactile (Conway & Christiansen, 2005) and auditory regularities (Saffran et al., 1999), all of which have been expressed in terms of a domain general mechanism that has been extensively investigated across several fields of inquiry, including memory (Kóbor et al., 2017), object representation (Lengyel et al., 2019), predictive processing (Morgan et al., 2019), and language acquisition (Saffran & Kirkham, 2018).

It is nearly undeniable that statistical learning mechanisms can be associated with skilled reading. Effects of orthographic redundancy (i.e., co-occurrence of letters and letter chunks e.g., D'ydewalle & Auwers, 1994), constitute the bedrock of visual word identification (Massaro et al., 1981; see, e.g., Chetail, 2015 for a recent review). A clear example comes from word frequency effects (Monsell et al., 1989; Preston, 1935; for a recent review, see Brysbaert et al., 2018): word frequency alone can account for about 40% of the variance in lexical decision times (Brysbaert & New, 2009), and has been considered a proxy for how experience can modulate word representations and recognition. Word frequency effects have also been investigated in relation to sublexical factors, for instance through the modulation of stem frequency (e.g., Baayen et al., 1997; Burani et al., 1984; Colé et al., 1989; Giraudo et al., 2016; Taft, 1979). Previous experience with the regularities embedded in the language is also attested as frequency effects for single letters (Mason, 1978; New

& Grainger, 2011), and letter transitional probabilities (Rumelhart & Siple, 1974; Smith, 1969).

Supra-letter, sub-word units yield a more inconsistent set of experimental results, as emblematically exemplified by the case of bigrams. Frequently co-occurring pairs of letters have been controversially associated with facilitatory (e.g., G. B. Biederman, 1966), inhibitory (e.g., Owsowitz, 1943) and null effects (e.g., Andrews, 1992). Such a complex pattern of results has been recently revisited by Schmalz and Mulatti (2017) in a Bayesian analysis of large-scale databases. If highly frequent bigrams weakly inhibited visual word identification latencies from the English Lexicon Project (Balota et al., 2007), they had a no effect in data from the British Lexicon Project (Keuleers et al., 2012), a general picture that casts serious doubts on the role of bigram frequency in letter string processing. A different view is offered by Chetail (2015), which instead focuses on the relation between co-occurrence regularities and sub-lexical information (in keeping with, e.g., Crepaldi et al., 2010; R. Frost, 2012). Both the nature and the grain size of letter patterns can only be informative if considered in tandem with the structure of a given language, with its ortho-phono-morphological associations. Beyond any language-agnostic definition of potentially relevant units like bigrams and trigrams, the statistical properties of written input hold cardinal information for skilled readers to utilize, and might influence several key aspects of visual word identification.

Further evidence in this direction comes from the statistical learning literature. In addition to studies connecting literacy acquisition and second language learning with statistical learning abilities (e.g., Arciuli & Simpson, 2012; R. Frost et al., 2013), learning experiments with skilled readers successfully replicate some key findings in visual word recognition, across lexical and sublexical dimensions. For example, Chetail (2017) exposed readers to a lexicon of pseudo-characters, in which some pairs of symbols occurred with a high frequency. As a result, when participants were exposed to novel items, they judged the stimuli comprising high-frequency bigrams to be more word-like. This finding replicates a pattern attested in developing readers, with studies such as Pacton et al. (2001) showing that French-speaking first-graders tend to judge items that better represent real words' distributional statistics as more plausible.

A similar contribution comes from another learning study, conducted by Lelonkiewicz et al. (2020). Participants familiarized themselves with non-alphabetic stimuli comprising affix-like chunks, defined as frequently co-occurring clusters of symbols consistently appearing either at the beginning or at the end of strings. A following testing phase showed an emerging sensitivity to the presence of "affixes" in novel strings, particularly if appearing in the same position as during familiarization. Position-specificity is a crucial feature of affix processing in skilled reading, as clearly attested by Crepaldi et al. (2010), which showed that suffixed nonwords are rejected more slowly only if the suffix appears in it typical position (i.e., *ful-gas* and *fil-gas* are equally easy to reject, while *gas-ful* is markedly harder to reject than *gas-fil*).

For these and many more pieces of evidence, sensitivity to patterns of regularity should amount to a linchpin of any account of reading (R. Frost, 2012), so that our understanding of visual word recognition can be informed by the fundamental cognitive mechanisms subsumed under the umbrella of statistical learning.

1.4 Statistical Learning and Domain-Generality in Visual Word Processing

The promise of a simple, general and universal mechanism that could tune visual word processing abilities is consistent with the fact that, astonishingly, literacy is a relatively recent cultural invention, first emerged around five thousand years ago (Carr, 1999) and independently achieved by different human cultures. As a consequence, reading constitutes an expert system that is likely to rely on cortical architectures deputed to other skills, such as learning, memory and visual recognition (Dehaene & Cohen, 2007).

From a neurobiological point of view, visual word identification could definitely be supported by general-purpose mechanisms that are closely related to sensitivity to statistical regularities. Particularly, as postulated by the Local Combination Detector model (LCD, Dehaene et al., 2005) visual word recognition processes would be governed by the same principles that organize the primate ventral visual system, with progressively larger visual receptor fields tuned to respond to increasingly complex visual objects (a structure that has also been attested in the macaque brain, Baker et al., 2002). In the case of reading material, the exposure to linguistic patterns would result in familiarity with letter co-occurrence regularities, on the basis of which a hierarchy of neuronal units would acquire preference to letters, letter-chunks and eventually whole words. Such a cascade of statistically coherent, familiar visual objects amounts to the visual word-form system, which indeed shows a graded preference for increasingly familiar stimuli, from false-font strings to frequent quadrigrams, in an anterior-to-posterior progression of selectivity within the occipitotemporal cortex (Vinckier et al., 2007).

Experiments with non-human species made a decisive contribution towards linking visual word processing and perceptual abilities under the umbrella of statistical learning. In a study by Grainger et al. (2012), baboons were exposed to orthographic material, comprising four-letter English words along with carefully structured nonword stimuli. In less than two months, the primates learned to correctly discriminate lexical items. More importantly, they began to generalize their knowledge to novel stimuli, showing that they successfully extracted and internalized the statistical structure of the language they had been exposed to. Similar results have been achieved in pigeons (Scarf et al., 2016), a species with a visual system that is markedly more distant from the human one, both phylogenetically and organizationally.

The idea that the reading system exploits a deeper and more ancestral set of visual statistical learning mechanisms is also supported by a recent study conducted by Y. Vidal et al. (2021), in which (human) skilled readers were presented with strings of letter-like symbols exhibiting a reliable regularity (i.e., frequent bigrams). As a result, participants implicitly picked up co-occurrences between symbols, and constructed an expectation towards the 'well-formedness' of the items they had been passively exposed to. Notably, this finding is not only reminiscent of the animal literature, but it also replicates the aforementioned pattern attested in developing readers (Cassar & Treiman, 1997; Pacton et al., 2001). Crucially, the the work by Vidal and colleagues suggests that the scope of such sensitivity extends even beyond language and language-like material, as pairs of co-occurring features are exploited also in three-dimensional objects and sinusoidal gratings, in which the hidden regularity was realized through frequent pairs of specific levels of contrast, spatial frequency and orientation.

1.5 What (else) can Statistical Learning offer to Reading?

In a wealth of investigations, the reading literature, and more generally the study of language processing, have greatly benefited from the statistical learning framework. Historically, domain-specificity and innate knowledge have been preeminent topics of debate in linguistic research (Chomsky, 1980, 2011; Gallistel, 2011). Experimental findings supporting an experience-dependent mechanism that is intimately tuned to regularities induced a pronounced emphasis on learning *per se*, in what amounts to an authentic theoretical shift in the approach to language processing. Nevertheless, surprisingly little is known as to how this pervasive sensitivity to the statistical structure in the (textual) environment informs visual word identification and reading.

As critically noted by R. Frost et al. (2019), most of the research on how organisms detect and encode regularities has been somewhat circular, with experimental and computational evidence "[. . .] offering yet again an existence proof that regularities can be learned" (R. Frost et al., 2019, p. 1135). In a way, our understanding of such a crucial phenomenon has been confined to a relatively narrow set of rather artificial experimental paradigms, such as Artificial Grammar Learning (AGL, Reber, 1967) and Serial Recall Task (SRT, Karpicke & Pisoni, 2004). Additionally, most investigations exhibit little variation in the kind of regularities manipulated, which tend to be rather simple and based on fully deterministic rules, as illustriously exemplified in the work by Saffran et al. (1996). In this study, infants were shown to segment continuous speech streams on the basis of transition probabilities between syllables; particularly, within-word transitions of subsequent syllables would be perfectly systematic (100% probability), hence providing a powerful cue if compared to the much more unlikely between-word transitions (33%). Several investigations followed throughout the years, leading to a somewhat consolidated practice of adopting similar materials and methods. Notwithstanding all the decisive scientific advancements achieved, this approach risks to severely reduce the kind of phenomena that can be ascribed to statistical learning. Consequently, and together with the substantial lack of an uncontroversial definition, such a crucial cognitive mechanism is sometimes confined to mere sensitivity to transition probabilities.

From the lack of a clear definition stems another possible path that leads the opposite extreme, that is, reducing everything to statistical learning mechanisms. While it is plausible that sensitivity to quantifiable regularities plays a major role in several cognitive functions, rendering statistical learning a cognitive passe-partout can cause its predictive value to drop dangerously, and with it the chance of gaining a deeper understanding of other phenomena that might be linked to it to some extent.

Both reductionist (i.e., confining statistical learning to a specific set of experimental manipulations) and holistic (i.e., assuming everything is informed by statistical learning) views of this mechanism substantially affect any chance of assessing its prospective implications in visual word identification. The complexity of real languages cannot be fully captured by the carefully controlled artificial grammars created in the statistical learning research, which generally focus on a finite and well-defined set of regularities (as dutifully noted in, e.g., Bogaerts et al., 2020). Alternatively, a broader view of statistical learning contributes to a domain-generality (even if applied within the boundaries of modality-specificity, R. Frost et al., 2015) that allows reconciling the young reading system to more ancestral, perceptual skills. But can this framework foster novel insights into visual word recognition, specifically? Or should reading be framed simply as a manifestation of the brain's visual statistical learning capacities? The tight connection between textual and statistical regularities, investigated and reported yet again in years of research, does indeed raise the question of where (and whether) to draw the line between linguistic knowledge and familiarity with textual statistics. Plausible word forms, but also legal ortho-phonotactic patterns, syllables and morphemes, are all examples of significant linguistic regularities that are also rich in statistical cues for the brain to exploit. What can be labeled as *implicit statistical learning* (Christiansen, 2019) could be the key to unlocking some of the fundamental open questions in visual word identification, such as what the minimal information units in language might be and how they should be defined, in the interplay of visual, statistical and linguistic factors.

In keeping with these considerations, the present work intends to look at reading through the lenses of statistical learning while steering away from both reductionist and holistic accounts of this indubitably fundamental cognitive resource. Particularly, (*implicit*) *statistical learning* and *statistical learning mechanisms* are terms here adopted to refer to the general sensitivity to statistically quantifiable regularities. Different patterns of regularity were considered within the scope of linguistic phenomena pertaining early visual word recognition (such as morphological and orthographic processing), with the aim of offering a window into skilled reading.

1.6 Research Questions and Roadmap

The overarching question addressed in the present thesis is how statistical learning and regularity detection relate to visual word identification. In particular, we asked whether a lifelong experience with the hidden, recurrent structures in the language affects the earliest stages of visual word identification, and whether some of the fundamental skilled reading phenomena reported in the literature are rooted in visual statistical learning mechanisms. Structurally, this thesis is composed as a collection of manuscripts, with each chapter independently detailing a study tackling specific experimental questions.

Chapter 2 describes a behavioral study of morpho-orthographic regularities, an extensively researched topic in the field of visual word identification (Amenta & Crepaldi, 2012; Rastle & Davis, 2008). Morphemes are recurrent letter chunks that convey a fairly predictable form-to-meaning mapping, and as such they are considered *islands of regularity* (Rastle et al., 2000) that could efficiently mediate lexical access. Masked priming lexical decision studies (Forster & Davis, 1984) provide evidence for morpheme identification in complex words, such as *sing-er*, and nonwords, like *basket-y*. Curiously, a consistent set of experiments indicates that morphemes are recognized even in contexts that lack morphological complexity, such as *corn-er*, where *-er* is not conveying any meaning, and there is no semantic relation between the words *corner* and *corn*. Why would the reading system exploit the mere appearance of morphological complexity in achieving word identification? In search of an explanation for such counter-intuitive phenomenon, we investigated whether morpheme recognition could actually be rooted in the visual system's sensitivity to statistics of letter co-occurrences. To this aim, we assessed masked priming as induced by nonword primes obtained by combining a stem (e.g., *bulb*) with (i) naturally frequent, derivational suffixes (e.g., *-ment*), (ii) non-morphological, equally frequent word endings (e.g., *-idge*), and (iii) non-morphological, infrequent word endings (e.g., *-kle*). In two additional tasks, we collected interpretability and word-likeness measures for morphologically structured nonwords, to investigate whether priming can be modulated by such factors. We observed a statistically comparable facilitation elicited by the three nonword types, suggesting that neither frequency nor morphological status of word-endings affects masked morphological priming with nonword primes, a pattern that was not affected by interpretability nor word-likeness. This result was replicated in a second masked priming experiment with a new set of items including *corner-corn* prime-target pairs, and is in line with models of early visual processing based on automatic stem/word extraction (e.g., Grainger & Beyersmann, 2017).

The study described in Chapter 3 was designed to further attempt a qualification of the respective contributions of form and meaning-based regularities. We exposed skilled readers to both suffixes (e.g., *ment*) and frequent word endings (e.g., *idge*) in isolation, in a Fast Periodic Visual Stimulation (FPVS, Rossion, 2014) design. FPVS is a behavior-free paradigm that combines electrophysiological recordings with oddball presentation sequences, to provide objective neural signatures of discrimination processes. Streams of visual stimuli (i.e., base stimuli, e.g., consonant strings) that are presented at a frequency rate F are interleaved with oddballs (i.e., stimuli from another category, e.g., words), which are periodically inserted at fixed intervals (every n items), thus appearing at a slower frequency rate (i.e., F/n). A general neural entrainment to the periodic visual stimulation is indexed by a response at the base stimulation frequency F. Of particular interest is the presence of a neural response at the predefined oddball stimulation frequency F/n, as it can be taken to reflect the brain's ability to discriminate between the two types of stimulus categories, and is selective to the dimension that differentiates the oddball from the base stimuli. Our study adopted magnetoencephalography (MEG) with FPVS sequences carefully constructed to reveal selective discrimination responses for specific linguistic features, to assess their relevance in skilled reading. We investigated the presence of an Alphabetic response, by comparing strings of artificial characters (rendered through the BACS-2 font, C. Vidal & Chetail, 2017), with strings of consonants (e.g., *sfcl*). The same strings of consonants were then contrasted with readable, but non-existing strings (e.g., *amsi*), to test the relevance of Readability. Readable items were pitted against meaningless word endings that are highly frequent in the written language (e.g., *enso*, comparable to the English *idge*), to investigate the impact of Familiarity. Frequent units were then set against suffixes, (e.g., *eria*, similar to the English *ment*), so that we could assess the role of Meaningfulness. Finally, suffixes were compared with words (e.g., *idea*), to obtain a purely lexical response, in that the two classes differ solely on their lexical status. Non-parametric cluster permutation tests (Maris & Oostenveld, 2007) at sensor level indicated a clear discrimination for alphabetic (i.e., strings of consonants compared to pseudo-characters) and lexical items (i.e., words, as opposed to suffixes). Source level investigations on a predefined set of regions revealed a more complex picture. All of the more subtle differences along our stimulus hierarchy led to clear neural responses, with the sole exception of suffixes compared to highly frequent endings. This null result was further investigated through a Bayes Factor analysis, which moderately supported the lack of a distinction between suffixes and highly frequent, meaningless word-endings, at least as captured in the context of the FPVS paradigm.

From the work described in Chapter 3 emerged the auxiliary hypothesis at the core of Chapter 4. An FPVS stimulation stream, with its rigid structure and periodic rhythm, is potentially rich in statistical cues to uncover. Since the very nature of the paradigm requires oddballs to deviate from a standard, in each sequence tokens belonging to one category might be presented relatively less often compared to the other. This difference in the number of repetitions induces a regularity that could be implicitly captured by the brain, eliciting the emergence of visual discrimination responses. Chapter 4 describes a study that tested this conjecture by collecting electroencephalography (EEG) recordings while skilled readers were exposed to sequences of items belonging to the same category (e.g., words in streams of words). We manipulated the relative frequency of individual tokens in the presentation stream, which allowed us to study whether neural responses can be induced by incidental statistical learning within a short presentation, for stimuli belonging to the same category. With this logic, we constructed homogeneous sequences of four types of linguistic items with decreasing familiarity (from pseudo-characters to words), thus aiming at investigating how different levels of orthographic structure (i.e., whole-word level, co-occurring letter clusters, letters, letter features) would impact learning. Both region-of-interest and cluster-permutation based frequency-domain analyses in sensor space revealed robust neural responses at the oddball presentation rate in all conditions, reflecting the discrimination between two locally emerged groups of items purely informed by token frequency. These results provide evidence for a fundamental frequency-tuned mechanism that operates under high temporal constraints, and that could underpin the bootstrapping of linguistic categories (Ellis, 2002; Maye et al., 2002).

Chapter 5 presents a collection of experiments investigating whether the statistical regularities inherent in the natural language can influence letter perception. Orthographic processing comprises the set of operations by which the reading brain capitalizes on letter identity and position to derive larger linguistic units (e.g., morphemes, words), and as such it involves a close interaction of linguistic and perceptual processes (Grainger, Dufau, & Ziegler, 2016). Higher level knowledge plays a pivotal role in this phenomenon, with top-down, lexical representations inducing letter perception enhancement (Heilbron et al., 2020). One largely unexplored hypothesis is for such facilitation to interact with letter co-occurrences as expressed in the language. Particularly, we built on the perceptual effects of absolute position within letter-strings (Castet et al., 2017; Stevens & Grainger, 2003; Tydgat & Grainger, 2009) to test whether statistical regularities can improve performance in spite of visual bottlenecks (e.g., crowding, Pelli et al., 2004; Pelli et al., 2007). Skilled readers were briefly exposed to strings of five consonants; critically, letters in position 2 and 4 were embedded in transitional probability triplets that could either be high (e.g., G**L**VTZ) or low (e.g., N**L**RTZ) as quantified in an Italian corpus. When presented with two strings differing by the critical letter (G**L**VTZ vs. G**R**VTZ, in a task similar to Adelman et al., 2010), participants identified the correct option more often in triplets that reflected the language's distributional properties. The introduction of response time constraints caused the effect to disappear entirely when the task required identifying single letters, in a more traditional Reicher-Wheeler task (Reicher, 1969; Wheeler, 1970). Facilitatory patterns induced by high transition triplets survived in a Same-Different matching task, as faster correct responses for position 2. This shows that letter identification is affected by letter co-occurrence statistics, but only when the task emphasizes string rather than letter processing, and coherently with a rapid deployment of spatial attention towards the beginning of letter strings (Aschenbrenner et al., 2017). The genuine orthographic nature of this effect was further corroborated by a lack of facilitation when the same matching task was performed on strings of non–alphabetic characters sharing low-level visual features with letters (i.e., symbols from the BACS-2 font, C. Vidal & Chetail, 2017).

Chapter 2

Study I: Letter Chunk Frequency in Morphological Masked Priming[*]

Reading is a critical skill in our everyday life, and for skilled readers the processing of linguistic input unfolds rapidly and effortlessly. In search of the building blocks at the basis of such phenomenon, the literature is rich in studies placing special consideration on morphemes, the smallest meaning-bearing units in language (Bloomfield, 1933). Morphemes introduce a fairly regular form-to-meaning mapping, and thus provide predictable patterns that could be efficiently exploited for lexical processing (e.g., Bybee, 1988; Castles et al., 2018; Taft & Forster, 1976).

Consistent evidence encompassing many languages and experimental paradigms suggests that morphology does indeed play a role during the earliest stages of visual word identification (for reviews, see Giraudo & Voga, 2014; Rastle & Davis, 2008), even if there is little consensus on the fundamental mechanisms that are in place at such level of processing (Amenta & Crepaldi, 2012). Specifically, results from masked priming studies (Forster & Davis, 1984) indicate that embedded stems are indeed recognized within their derived

---

[*] From De Rosa, M., & Crepaldi, D. (2021). *Letter chunk frequency does not explain morphological masked priming.* Manuscript accepted for publication in *Psychonomic bulletin & review.*

forms (e.g., *sing* in *singer*). The strong and consistent facilitation elicited by such prime-target pairs is larger than the priming elicited by pairs that merely share some orthographic overlap (e.g., *twin* and *twinkle*), suggesting a morphological locus for the effect. Notably, a more controversial contrast is offered by words like *corner*, which under specific experimental conditions seem to undergo morphological analysis, leading to the somewhat counter-intuitive recognition of an embedded "stem" (i.e., *corn* within *corner*, Longtin et al., 2003; Rastle et al., 2004).

The existence of such "morpho-orthographic" effects has been theoretically interpreted under two main types of conceptual framework. An intriguing proposal came from computational work (e.g., Baayen et al., 2011), which capitalizes on discriminative learning in the context of a mapping effort between orthography and semantics, and provides evidence for morphological effects without explicit morpheme representations (i.e., -*er*). Crucially, morpho-orthographic effects are here considered a by-product of residual morpheme interpretability in opaque words, which is often supported by diachronically genuine relationships (e.g., *archer* and *arch*, from the Latin *arcus*) that could carry some degree of semantic transparency. Nevertheless, this account has been experimentally challenged by data exhibiting morpho-orthographic effects in unambiguously semantically opaque prime-target pairs (Beyersmann, Ziegler, Castles, et al., 2016).

Alternatively, several theoretical accounts postulate morpho-orthographic processing to depend on explicit levels of representation, with earlier proposals offering morphology itself as a primary organizational principle (e.g., Rastle & Davis, 2003; Taft, 1994). However, most of these models do not reckon with recent evidence coming from nonword primes, which produce strong facilitation even without a complete morphological structure (e.g., Beyersmann, Casalis, et al., 2015; Beyersmann, Cavalli, et al., 2016; Grainger & Beyersmann, 2020; Hasenäcker et al., 2016).

More recently, the emphasis switched away from morphology *per se* and more attention was put on letter statistics (e.g., Crepaldi et al., 2010; Grainger & Ziegler, 2011). The key insight in this respect is that morphemes also constitute recurrent letter strings in the written language: because they carry some meaning, morphological stems and chunks like *-ment*, *-ness* or *-er* occur relatively frequently across several different words, and therefore might become fairly salient units also from a merely orthographic, statistical point of view.

In support of this conjecture, sensitivity to statistical regularities is known to be an extremely powerful cognitive resource recruited in information processing in general (for recent reviews, see Armstrong et al., 2017; Aslin, 2017; Christiansen, 2019; R. Frost et al., 2019; Thiessen et al., 2013), and in reading in particular (e.g., Arciuli & Simpson, 2012; Chetail, 2015; Sawi & Rueckl, 2019; Schubert et al., 2020; Treiman et al., 2014). Recent experimental evidence in the context of the statistical learning framework substantiated the relationship between sublexical units and statistical patterns (e.g., Chetail, 2017; Lelonkiewicz et al., 2020). In particular, Lelonkiewicz et al. (2020) modelled morpheme learning in an artificial lexicon where the only possible cues were characters' statistics. When passively exposed to strings of pseudo-characters, skilled readers rapidly developed sensitivity to patterns of affixation on the basis of their frequency of occurrence. Crucially, the carved prefix and suffix-like units could not benefit from phonological or semantic information, and yet they exhibited some typical aspects of affix processing (i.e., positional constraints, Crepaldi et al., 2010). Frequency of occurrence is indeed a pivotal feature for language learning (e.g., Ellis, 2002), and frequency effects have often been considered proxies of learned representations in lexical decision studies (Baayen et al., 2007; Burani & Thornton, 2003; Colé et al., 1989; Taft, 1979, 2004). These considerations strengthen the idea that the "corner-corn" effect – and, more generally, morpho-orthographic chunking – might be based on the letter statistics that morphemes typically show, and particularly their frequency of occurrence. Some investigation of this hypothesis was carried out by Beyersmann, Ziegler, and Grainger (2015), who failed to observe a cluster frequency effect in a letter search task. This clearly speaks against the idea that the frequency of letter chunks is a primary driver during visual word identification. However, letter search is not the paradigm where morpho-orthographic effects are typically found, and the efficacy of this task in addressing morphological processing has been recently questioned (Hasenäcker et al., 2021).

To address these issues, we carried out a masked priming, lexical decision experiment with nonword primes. Specifically, we assessed the facilitation elicited by morphologically structured primes (e.g., *bulb-er*), and by non-morphologically structured nonwords whose endings were either as frequent (e.g., *bulb-le*) or consistently less frequent (e.g., *bulb-ew*) than suffixes. This manipulation allowed us to determine whether morpho-orthographic analysis stems from written frequency, or is rather subordinate to word-endings' morphological status.

Morphologically structured nonwords may lend themselves to some plausible semantic interpretation (e.g., *idealike*, *heroable*; Günther & Marelli, 2020), which could in turn influence masked priming (e.g., Heathcote et al., 2018). To test for such a possibility, after the main task participants were asked to provide interpretability ratings for the morphologically structured nonword primes. If facilitation could be explained by such interpretability ratings, this would suggest a role for the genuine morphological status of the suffixes/word-endings, rather than for their frequency.

Additionally, on the grounds of their structure, morphological nonwords can trigger activation into the lexical-semantic system, as indexed by the difficulty with which they are rejected in lexical decision tasks (*morpheme interference effect*; Beyersmann et al., 2020; Crepaldi et al., 2010; Taft & Forster, 1975; Yablonski & Ben-Shachar, 2016) and by their speed of processing in reading aloud (Burani et al., 2006). Therefore, an additional task was devised to estimate the interference induced by each morphological nonword, which could also affect masked priming; such eventual correlation might shed some light on how the masked priming results relate to the lexical-semantic system in its entirety.

2.2 Experiment I: Materials and Methods

Participants

Fifty-six Italian native speakers (19 males; age: M=24.86, SD=3.59) took part in the study after giving written informed consent. All participants had normal or corrected-to-normal vision and no history of linguistic or neurological impairment. They were compensated for their time, effort and travel expenses with a monetary reimbursement. The study was approved by the Ethics Committee at the International School for Advanced Studies, where participants were tested.

Masked Priming Lexical Decision Task

Materials Twenty-nine derivational Italian suffixes (e.g., *-mento*, English: *-ment*) were selected to have a fairly high token frequency (M=4.84, SD=0.61; length, M=3.82, SD=0.86). Meaningless word-endings (e.g., *-erso*) of comparable length (M=3.87, SD=0.33) were selected to construct a group of highly frequent (HF, M=4.94, SD=0.67) and one of infrequent (LF, M=2.33, SD=0.31) letter clusters, resulting in three sets of existing word-endings. Crucially, suffixes and highly frequent word-endings were of comparable token frequency, and differed solely on the basis of their morphological status; conversely, the low-frequency set of letter chunks consistently differed in terms of written frequency from the other two groups.

Seventy-eight nouns (e.g., *radio*, length: M=5.81; SD=1.12) were then selected as target words. The set of items was constructed to be fairly homogeneous in terms of written frequency (M=2.82, SD=0.45) and orthographic neighborhood size (OLD20, Yarkoni et al., 2008; M=1.36, SD=0.31). The stem of each target word was then combined with one letter cluster from each group of word-endings, thus resulting in 78 primes in each of three conditions: morphologically complex (Morph, length: M=8.70, SD=1.28; OLD20: M=2.60, SD=0.49; e.g., *radieria*), orthographic - high frequency (HF, length: M=8.75, SD=1.13; OLD20: M=2.90, SD=0.49; e.g., *radierso*) and orthographic - low frequency (LF, length: M=8.87, SD=1.08; OLD20: M=3.14, SD=0.44; e.g., *radieffa*). For each prime in each condition, an unrelated prime was obtained by combining the same ending to an unrelated stem (e.g., *bomberia-radio* acted as a control for *radieria-radio*). The unrelated primes were matched for both length and orthographic neighborhood size (Morph, length: M=8.70, SD=1.27; OLD20: M=2.61, SD=0.51; e.g., *bomberia*), orthographic - high frequency (HF, length: M=8.73, SD=1.13; OLD20: M=2.88, SD=0.51; e.g., *bomberso*); orthographic - low frequency (LF, length: M=8.87, SD=1.08; OLD20: M=3.14, SD=0.44; e.g., *bombeffa*). Seventy-eight nonword targets were then obtained by substituting one consonant from an Italian existing simple word and were adopted as filler items (e.g., *tafolo* from the word *tavolo*, table). Each nonword target was matched with a prime, constructed by adding the three-conditions clusters to a related or unrelated nonword base (e.g., *tafolmento-tafolo*, *taflement-tafle*, or *ritelmento-tafolo*, *retelment-tafle*).

The overall stimulus set was split into six sublists, following a within-item, within-subject Latin Square design, hence guaranteeing that participants were exposed to all conditions without seeing any target more than once.

Procedure Each trial began with a 500-ms string of hash marks, followed by the lowercase prime (50 ms) and the uppercase target, which remained on screen for 1500 ms or until response. Consecutive trials were separated by an interval jittered around 1500 ms. Sessions also comprised two examples, 12 practice and four warm-up trials, which were all excluded from the analyses.

Subsidiary tasks

Materials Morphological nonword primes, both related and unrelated, were further investigated through (i) an overt rating and (ii) an unprimed lexical decision task. These tasks were conceived to estimate any specific processing induced by the morphological nonword primes, either at an explicit level (i.e., through overt rating) or implicitly, via the delay on correct rejections in a lexical decision (*morpheme interference effect*; Beyersmann et al., 2020; Crepaldi et al., 2010; Taft & Forster, 1975; Yablonski & Ben-Shachar, 2016).

The rating task included for each participant the set of 26 nonwords that served as primes in the main task for that given participant; no filler items were used. Participants were asked to judge how easily they would be able to attribute a meaning to each nonword on a 1 (not interpretable at all) to 7 (easily interpretable) scale.

For the lexical decision task, each participant was shown the same 26 nonwords that served as primes in the main task. We additionally selected 26 derived Italian words to match the features and the structure of the morphological nonwords (e.g., *amicizia*, *friendship*; length: M=8.72, SD=1.27; OLD20: M=2.32, SD=0.54; written frequency: M=1.83, SD=0.87). The stimulus set comprised also 13 morphologically simple Italian words (e.g., *anguria*, *watermelon*; length: M=8.77, SD=1.83; OLD20: M=2.00, SD=0.69; written frequency: M=2.64, SD=0.61), and 13 nonwords obtained by substituting one consonant from an Italian existing simple word (e.g., *pafola*, from *parola*, *word*; length: M=8.46, SD=1.56; OLD20: M=2.55, SD=0.55).

Procedure The lexical decision trials began with a central fixation cross presented for 500 ms, followed by the uppercase target stimulus presented for 2000 ms or until response; consecutive trials were separated by a jittered interval of 1500 ms. In the rating task, the morphologically structured nonwords were presented one at a time in lowercase, and remained on the screen until response, without time constraints.

Apparatus

Participants were run individually in a soundproof experimental booth, seated at approximately 80 cm in front of a BenQ XL2720Z monitor (27”, 1920x1080 pixels, 144 Hz). They provided YES responses with their dominant hand (7 left-handed) through a Cedrus Response Pad RB-730. The experiment was administered via PsychToolbox-3 (Brainard, 1997; http://psychtoolbox.org/) on MATLAB R2015b (The Mathworks) in a Windows environment; stimuli were rendered as strings of Arial characters (32 pt), presented in white over a black background at the center of the screen.

Data Analysis

Main task (masked priming)

One target with an overall error rate over 30% was excluded from the analysis (*prua*, *prow*). One subject was below 80% in accuracy on nonword trials and was thus discarded. Anticipatory responses of less than 200 ms (1.66%), no-response trials (1.65%) and incorrect responses (3.64%) were also removed. Linear mixed-effects models with crossed random intercepts for subjects and target words (Baayen et al., 2008), as implemented in *lme4* (Bates et al., 2007) and *lmerTest* (Kuznetsova et al., 2017), were employed as the primary statistical tool.

The main analysis for the masked priming task was performed on inverse-transformed reaction times. The effects of interest were Relatedness (i.e., related vs. unrelated primes) and Condition (i.e., affixes, high-frequency endings and low-frequency endings), as well as their mutual interaction. In addition, we tested whether Relatedness interacted with the item-level metrics for interpretability and morpheme interference (see below); as non-morphemic primes do not have these metrics at all, this further analysis was carried out only on morphological primes. Other fixed effects were included if they significantly improved the model's goodness of fit in a backward step-wise model selection procedure, resulting in the inclusion of log-transformed target frequency, as well as accuracy and reaction time on the preceding trial.

Non-significant effects were further explored through Bayes Factor (BF) analyses (Dienes, 2014) as implemented in the R package *BayesFactor* (Morey et al., 2015). In particular, the preferred model (that is, the one expressing the hypothesis under study) was compared against models without the effects of interest, thus providing quantifiable evidence in support of H1 or H0.

Subsidiary tasks (ratings and morpheme interference)

Rating scores for the morphologically complex nonwords were transformed into within-subject z-scores:

$$z_{ij} = \frac{r_{ij} - M(r_j)}{SD(r_j)}$$

where r_{ij} is the rating given to item i by subject j, and $M(r_j)$ and $SD(r_j)$ are the mean and standard deviation across all ratings offered by subject j. These z-scores were then averaged across participants for each item, thus generating an item-specific metric for interpretability.

Reaction times for correct nonword rejections in the lexical decision task were again analyzed through linear mixed models, with Condition, target length and OLD20 as fixed effects, and crossed random intercepts for items and participants. Before modelling, we removed data from one participant with accuracy below 60%, no-response trials (0.36%) and incorrect responses (11.19% of total). Because all the other main sources of variance across nonwords were taken up by the fixed effects (e.g., length, orthographic neighborhood size), the random intercept for items was taken as an index of how much more (or less) morpheme interference any given nonword brings about. These two indices were used to model reaction times in the masked priming task for morphologically complex primes.

2.3 Experiment I: Results

The pattern of results in the main priming task is illustrated in Figure 2.1. The analysis of response times in the masked priming task resulted in a main effect of Relatedness (χ^2=46.926, p<0.001), indicating that related primes induced faster responses compared to their unrelated baseline. However, we

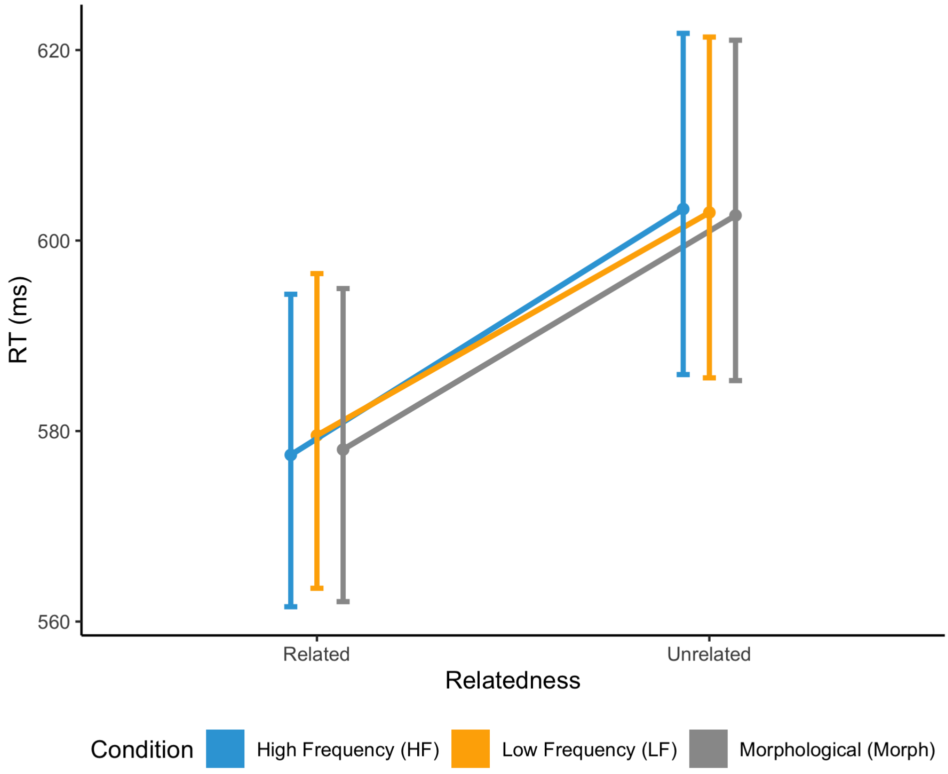


Figure 2.1: Model estimates of reaction times in the masked priming lexical decision task. Error bars depict 95% confidence intervals.

observe no effect of Condition (χ^2=0.313, p=0.855) nor an interaction between Condition and Relatedness (χ^2=0.547, p=0.761). A Bayes Factor analysis provided strong evidence against a model including an interaction (0.006±2.28%) or a main effect of Condition (0.002±2.5%). Therefore, the strong priming hereby observed is not influenced by either the frequency or the morphological status of the word-endings. Instead, the mere presence of the target stem in the prime seems enough to result in a consistent facilitation.

The morpheme interference task revealed a strong effect of Condition (χ^2= 12.576, p=0.0004), with morphological nonwords eliciting longer reaction times for correct rejections. The index obtained from this task yielded a rather moderate, albeit significant, correlation with the explicit ratings (r=0.23, $t(152)$=2.881, p=0.004, Figure 2.2A), thus indicating that both indices pinpoint distinct, although somewhat related phenomena. However, neither index affected priming (Figure 2.2B). The analysis of reaction times induced by morphologically complex primes showed a non-significant main effect of Morpheme Interference (χ^2=0.449, p=0.502), and a lack of interaction with Relatedness (χ^2=0.059, p= 0.806). A similar pattern was yielded by the model considering Explicit Interpretability (χ^2=2.088, p=0.148, interaction with Relatedness: χ^2=0.215, p= 0.642). Once again, these null results were corroborated through Bayes Factor analyses (Morpheme Interference: 0.042±2.09%; Explicit Interpretability: 0.022±1.71%).

2.4 Ad interim Discussion

The present experiment aimed at disentangling the role of co-occurrence regularities in morpho-orthographic effects. We combined existing Italian stems with genuine suffixes, high-frequency and low-frequency word-endings, and examined the facilitation elicited by each type of nonword in a masked priming, lexical decision study. A strong priming effect emerged independently of either frequency or the morphological nature of word-endings. Coherently, the facilitation elicited by morphological nonwords (e.g., *heroable*) did not depend on rating-based semantic interpretability nor on how much morpheme interference effect they caused in a plain lexical decision task.

Following the suggestion of an anonymous reviewer, we tried to replicate these results in a second masked priming experiment that also included *corner-corn* prime-target pairs. The aim was twofold: to offer a self-replication, and to assess whether the inclusion of lexical primes could affect the observed pattern

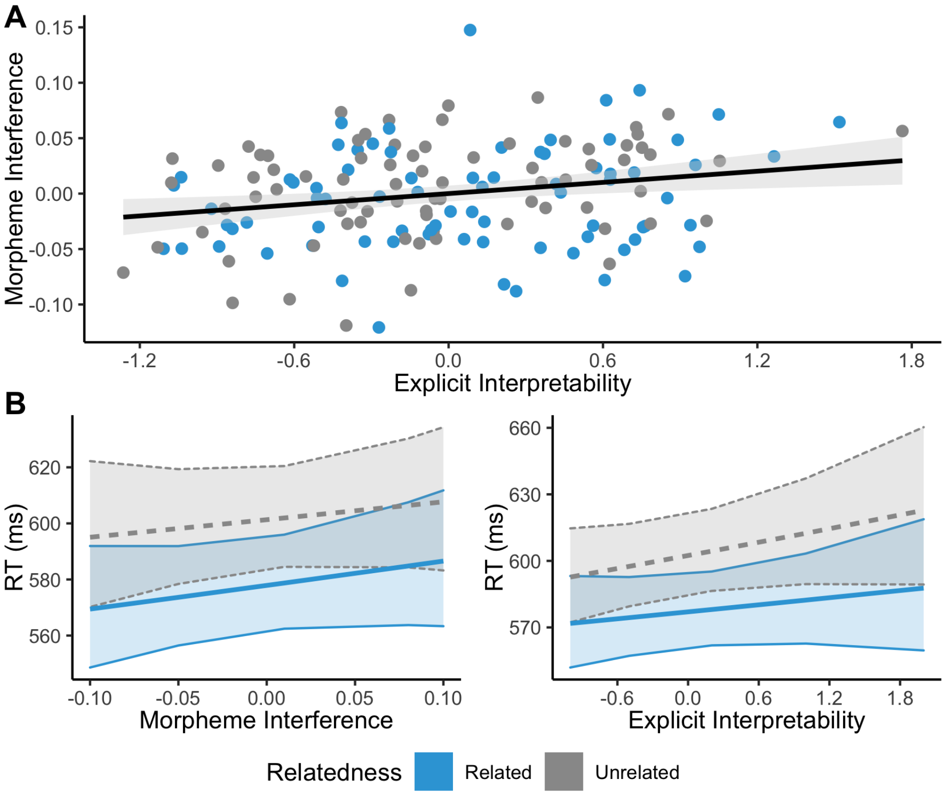


Figure 2.2: (A) Correlation between Morpheme Interference and Explicit Interpretability indices; (B) Estimated effect of both indices on masked priming reaction times. RTs increase slightly with growing Morpheme Interference/Interpretability (although the effect doesn't reach significance), but priming remains clearly constant. Shaded areas depict 95% confidence intervals.

of facilitation.

2.5 Experiment II: Materials and Methods

Participants

Forty-five Italian native speakers (14 males; age: M=26.08, SD=4.18) took part in the study after giving written informed consent. All participants had normal or corrected-to-normal vision and no history of linguistic or neurological impairment.

Materials

In addition to the three conditions explored in Experiment I, we included prime-target pairs of pseudo-derived words (e.g., *corner*) priming their pseudo-stem (e.g., *corn*) – the classic morpho-orthographic priming condition (Longtin et al., 2003; Rastle et al., 2004). The inclusion of word primes did not allow to construct a stimulus set that would satisfy all the relevant formal constraints in a within-item design; consequently, we made use of different target words in the four conditions. More specifically, 40 words (e.g., *rosa*, English: *rose*) were selected for each condition, matched for length, frequency and orthographic neighborhood size (Table 2.1). The sets of targets were different but comparable across experiments.

Each target word was then paired with both a related and an unrelated prime, coherently with the assigned condition. Targets in the opaque condition were paired with pseudo-derived word primes (e.g., *cervello-cervo*, comparable to *corner-corn* in English). Nonword primes were obtained with the same logic of Experiment I, that is, by combining the stems of the selected tar-

Condition	Frequency	Length	OLD20
High Frequency (HF)	3.645 (0.738)	5.05 (1.011)	1.141 (0.282)
Low Frequency (LF)	3.615 (0.722)	5.025 (1)	1.176 (0.296)
Morphological (Morph)	3.611 (0.786)	5.025 (0.862)	1.176 (0.316)
Opaque - Word (Op)	3.614 (0.765)	4.975 (0.768)	1.124 (0.228)

Table 2.1: Target features (mean and standard deviation) in Experiment II.

gets with suffixes (e.g., *-eria*; frequency: *M*=5.10, *SD*=0.47; length: *M*=3.9, *SD*=0.71), highly frequent, meaningless word-endings (e.g., *-upe*; frequency: *M*=5.08, *SD*=0.32; length: *M*=3.82, *SD*=0.39) and low frequency, meaningless word-endings (e.g.,*-iaba*; frequency: *M*=2.60, *SD*=0.82; length: *M*=3.85, *SD*=0.36). Overall, we constructed one set of word primes and three sets of nonword primes, which were matched for length and orthographic neighborhood size and paired with carefully constructed unrelated baselines (Table 2.2).

Condition	Relatedness	Frequency	Length	OLD20
High Frequency (HF)	Related	0	7.85 (1.231)	2.466 (0.552)
High Frequency (HF)	Unrelated	0	7.875 (1.223)	2.461 (0.522)
Low Frequency (LF)	Related	0	7.825 (1.196)	2.752 (0.495)
Low Frequency (LF)	Unrelated	0	7.875 (1.223)	2.692 (0.582)
Morphological (Morph)	Related	0	7.85 (1.231)	2.244 (0.574)
Morphological (Morph)	Unrelated	0	7.85 (1.231)	2.215 (0.637)
Opaque - Word (Op)	Related	2.624 (0.767)	7.85 (1.231)	1.742 (0.442)
Opaque - Word (Op)	Unrelated	2.657 (0.902)	7.825 (1.238)	1.709 (0.432)

Table 2.2: Prime features (mean and standard deviation) in Experiment II.

As a result, the stimulus set was made up of 160 target words, each paired with a related and an unrelated prime, which were rotated across participants in a between-item, within-subject Latin Square design; note that this approach implies only two rotations, compared to the six rotations adopted in Experiment I.

One hundred and sixty nonwords were then obtained by substituting a consonant from an existing Italian simple word (e.g., *fuolo* from the word *fuoco*, *fire*). These items were used as NO-response targets in filler trials. Following the approach adopted in Experiment I, each nonword target was matched with a nonword prime, constructed by adding the same clusters as in experimental conditions to a related or unrelated nonword base (e.g., *fuolerpe*).

Procedure

The trial timeline was identical to Experiment I, with the sole exception of primes being presented more briefly (42 ms) to further ensure their effective masking.

Data Analysis

The analysis approach was identical to Experiment I in all details.

One subject was below 80% in accuracy on nonword trials and was thus discarded. No-response trials (0.32%) and incorrect responses (2.51%) were also removed. The final model included log-transformed frequency, orthographic neighborhood size and length of the targets, prime length as well as trial number within the session, accuracy and reaction time on the preceding trial.

2.6 Experiment II: Results

The results obtained from Experiment II are displayed in Figure 2.3, with primes from all conditions showing a facilitatory pattern (main effect of Relatedness, (χ^2=42.372, p<0.001). Critically, we replicate the lack of an interaction

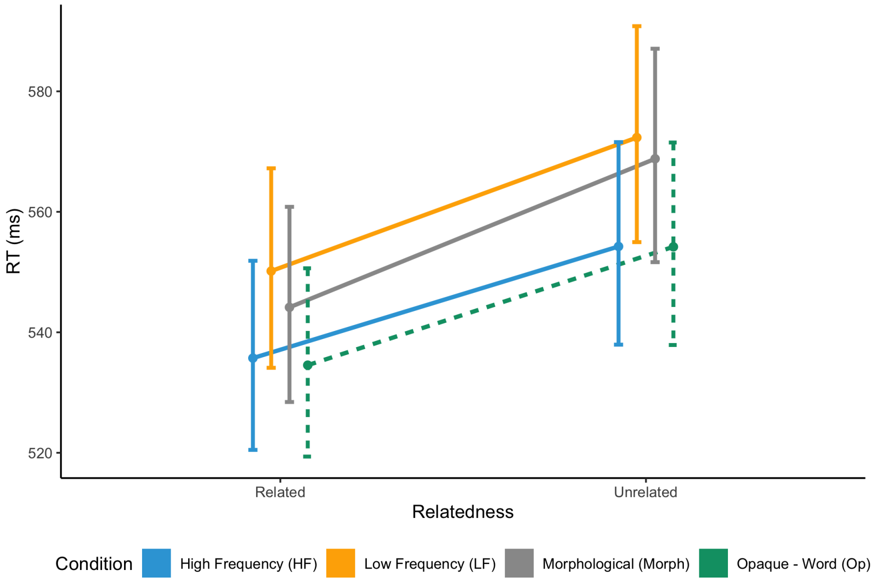


Figure 2.3: Model estimates of reaction times in Experiment II. Error bars depict 95% confidence intervals.

between Condition and Relatedness (χ^2=1.151, p=0.765). Such result is corroborated by a Bayes Factor analysis, which provides strong evidence against the model including an interaction factor (0.00082±3.09%).

2.7 Discussion

The present study aimed at establishing the relationship between morpho-orthographic effects and letter co-occurrence regularities. Since morphemes are also frequent letter clusters, we combined existing Italian stems with genuine suffixes, high-frequency and low-frequency word-endings, and examined the facilitation elicited by each type of nonword in a masked priming, lexical decision study. A strong priming effect emerged independently of either frequency or morphological nature of word-endings. Such pattern of results was further corroborated through an additional experiment including lexical primes with semantically opaque relations to their targets (e.g., *corner-corn*).

Coherently, the facilitation elicited by morphological nonwords (e.g., *heroable*) did not depend on rating-based semantic interpretability nor on how much morpheme interference effect they caused in a plain lexical decision task.

The main results of the masked priming task are in line with a wealth of studies on nonword primes, which consistently reported solid facilitation effects independently of the presence of an affix (that is, with primes like *farmness*, but also with primes like *farmald*; e.g., Beyersmann, Casalis, et al., 2015; Beyersmann, Cavalli, et al., 2016; Beyersmann & Grainger, 2018; Hasenäcker et al., 2016, 2020; Heathcote et al., 2018; McCormick et al., 2009; Morris et al., 2011). It is noteworthy that such a pattern is different from the solidly replicated evidence coming from word primes, in which the presence of both a (pseudo-)stem and a (pseudo-)affix is necessary to elicit facilitation (*corner* primes *corn*, but *brothel* does not prime *broth*; e.g., Rastle et al., 2004). This asymmetry between word and nonword primes could be quite easily accounted for by lexical competition. While nonword primes have no established representations, words might compete for activation in the lexical-semantic system: *corner* and *cornea* would be competing with *corn*, but neither *cornity* nor *cornew* would. Therefore, if morphology becomes crucial to overcome competition and win the race for activation in word priming (i.e., allowing *corn* to be activated in *corner*, but not in *cornea*), the embedded target word can be easily activated in a nonword prime by virtue of its mere presence (e.g., Grainger & Beyersmann, 2017). This early activation of shared elements between primes and targets could arise from different mechanisms, as implemented by several models in the literature. For instance, Grainger and Beyersmann (2017) suggest that such a mechanism is deputed to the extraction of edge-aligned embedded words; on the other hand, Crepaldi et al. (2010) and Taft (2004) stipulate the existence of a pre-lexical level of representation that would capture both stems and affixes.

While the present results are largely compatible with either account of stem extraction, they clearly speak against morphology *per se* as the main driver of the early stages of visual word identification, as postulated by earlier models of pre-lexical processing (e.g., Crepaldi et al., 2010; Taft, 2004; Taft & Nguyen-Hoan, 2010). Instead, our findings are better aligned with more recent theories that emphasize orthographic, rather than morphological factors. The hypothesis at the core of the present study is that morpho-orthographic effects are mostly based on letter statistics; morphemes, among other letter chunks, are frequent letter clusters, and this is why they would be captured at this level of processing. This account is coherent with recent findings reported by Grainger and Beyersmann (2020), suggesting that in the absence of a pseudo-morphological structure, nonword priming might be affected by conditional probabilities between the identified stem and an eventual (derivational) affix.

However, the statistical regularity manipulated in the present study (i.e., word-ending frequency) did not affect morpho-orthographic priming, a result that is also consistent with previous evidence coming from letter search studies (Beyersmann, Ziegler, & Grainger, 2015). Despite its essential role in linguistic processing (e.g., Ellis, 2002), letter-cluster frequency should be regarded as only one possible metric of letter co-occurrence regularities. It is hence possible for other, more sophisticated metrics (such as the aforementioned conditional probability) to play a more prominent role in early visual word processing. This would in turn suggest the involvement of a different mechanism, perhaps of a predictive nature (e.g., Avarguès-Weber et al., 2020), as suggested by several experiments across different cognitive domains (see R. Frost et al., 2019, for a recent review on the history and interplay of co-occurrence metrics).

The primary role of statistical cues, rather than morphological status *per* *se*, is also widely supported by some evidence obtained in artificial lexicon studies (e.g., Chetail, 2017; Lelonkiewicz et al., 2020), in which readers were unequivocally shown to be sensitive to the frequency with which chunks of pseudo-characters co-occur. One key difference is in the nature of the tasks adopted, as well as in the experimental demands of these studies. Specifically, learning studies with artificial characters focus on unfamiliar material that becomes somewhat familiar by the end of the experiment. Since the pioneering work of Saffran et al. (1996), the extraction of statistical information has in fact proven to be the bedrock behind the learning of linguistic (or pseudo-linguistic) material, with frequency of occurrence having a pivotal role during the first phases of exposure to novel stimuli. The goal of the present study was instead to uncover the role of co-occurrences within the processing of well-established units (existing letters and morphemes). It is possible, then, that while growing in familiarity and proficiency with a writing system, letter statistics contribute to create and consolidate higher-level representations, a stage that would be captured by artificial lexicon studies. Once such higher-level representations are well established, they would acquire an autonomous, rooted status, thus making the system less reliant on mere frequency (and perhaps other statistical cues, more generally); this would be the stage captured here, and in other studies with real linguistic material. The frequency of letter chunks would be critical during learning, but perhaps less so in the mature system, where those chunks have probably acquired representations on their own.

This interpretation highlights the idea that the early stages of visual word processing, even if they are indeed heavily based on language-agnostic, statistical processes, are also in constant interaction with more central, lexical representations (whenever these representations are available). This resolves the apparent conflict with data showing a role for morphological family size

(Beyersmann & Grainger, 2018) and position of the embedded stem (Beyersmann et al., 2018) in complex nonword priming effects.

An additional result is that nonword priming is not modulated by either lexical-semantic drive (as indexed by the amount of morpheme interference), or interpretability (as gauged by overt ratings). Importantly however, metalinguistic ratings constitute only one possible operationalization of nonword interpretability. Compelling evidence for more sophisticated, model-based metrics comes from work on novel compounds (Günther & Marelli, 2020), in which semantic effects are captured through compositional processes, an approach that paves the way for a more dynamic view of meaning-combination mechanisms in novel derived forms (Amenta et al., 2020). Nevertheless, in keeping with several previous studies (e.g., Giraudo & Voga, 2016; Longtin & Meunier, 2005; Tseng et al., 2020), the present results suggest that masked priming is not much influenced by semantic effects, at least with derived nonword primes (see, e.g., Feldman & Basnight-Brown, 2008; Feldman et al., 2012, for a somewhat different perspective with word primes). More generally, these data suggest a weak relationship between the mechanisms captured by masked priming, and the lexical-semantic dynamics induced by the same nonwords when presented overtly, as target items. Such results might indicate that while masked priming taps into early processing, overt-ratings and morpheme interference are based on subsequent stages, thus calling for an integrated view of morpho-orthographic phenomena within the lexical-semantic system at large.

Chapter 3

Study II: Selective Neural Entrainment Reveals Hierarchical Tuning to Linguistic Regularities[*]

In today's complex societies, printed words are among the most culturally relevant visual objects processed by the human brain, and visual word recognition is dexterously mastered by skilled readers, which can process written input as swiftly as faces. Nevertheless, the literate brain is a case of an expert system shaped by cultural experience (Dehaene & Cohen, 2011): while the cortical architectures supporting face processing might have evolved specifically to this aim, reading and writing constitute a relatively recent invention (Carr, 1999). Consequently, research around the neural underpinnings of reading poses rather peculiar challenges, tackled via developmental and neuropsychological studies, and encompassing several imaging and computational modeling efforts (e.g., Carreiras et al., 2014; Price, 2012).

Consistent evidence suggests the literate system relies on cortical resources originally deputed to other functions (e.g., visual object processing), which would be reorganized (or even recycled, Dehaene & Cohen, 2007), during liter-

---

[*] From De Rosa, M., Vignali, L., D'Urso, A., Ktori, M., Bottini, R., & Crepaldi, D. (2022). *Selective Neural Entrainment Reveals Hierarchical Tuning to Linguistic Regularities*. Manuscript in preparation.

acy acquisition (as reviewed in, e.g., Dehaene et al., 2015). As a result, the neural underpinnings of reading would still follow the principles that govern object recognition in the primate ventral stream (Dehaene et al., 2005). A clear example comes from the hierarchical organization observed in the macaque monkey, with an anterior-to-posterior progression of increasingly larger receptor fields for more complex objects (Booth & Rolls, 1998; Riesenhuber & Poggio, 1999; Rolls, 2001). A similar graded selectivity for increasingly complex linguistic stimuli was observed by Vinckier et al. (2007) in a portion of the ventral occipitotemporal cortex (vOT), with the asymmetrical left profile that is generally associated with linguistic processing (Cohen et al., 2002; Dejerine, 1892; Warrington & Shallice, 1980). Vinckier et al. (2007) exposed skilled readers to a hierarchy of linguistic stimuli, ranging from strings of pseudo-characters to real words, and including sequences of infrequent letters, frequent letters but rare bigrams, and frequent bigrams but rare quadrigrams. BOLD-contrast responses clearly indicated the presence of a hierarchical trajectory, with progressively selective responses for more complex stimuli. However, real words did not differ from highly frequent, ortho-phonotactically legal quadrigrams (i.e., pseudowords).

Albeit in line with previous evidence (J. R. Binder et al., 2006; Dehaene et al., 2005; Pammer et al., 2004; Price et al., 1996; Wydell et al., 2003), the lack of a reliable neural distinction between words and pseudowords has been object of a heated debate (as detailed in, e.g., Price, 2012; Taylor et al., 2013). Indiscriminate responses to real words (e.g., *rent*) and well-structured letter strings (e.g., *tren*), previously unseen and meaningless, suggest that visual word recognition might be entirely supported by abstract orthographic knowledge, consolidated by frequent encounters with regularly co-occurring patterns and beyond any lexical information. Such sublexical account (J. R.

Binder et al., 2006; Vinckier et al., 2007) has been challenged on the basis of studies showing selective lexical responses (Glezer et al., 2009; Kronbichler et al., 2007; Kronbichler et al., 2009), and proposing an interactive account of linguistic information, which would provide a source of top-down feedback for the early processing of orthographic input (Price & Devlin, 2003, 2011). Purely orthographic features, as well as higher-order factors (like phonology or semantics) and their mutual interaction, are then comparatively at the core of the neural computations performed in the literate brain. As a result, the rather refined knowledge of *where* the neural underpinnings of reading might reside is complemented by a relatively poor understanding of *what* such areas are coding for.

Notably, identifying the building blocks of visual word identification is a question of paramount importance also beyond the neuroimaging literature. The arena of cognitive models of reading is also populated by accounts that differently emphasize the role of linguistic factors and their relative contributions, even if they generally remain beyond the details of neural implementations (but see Taylor et al., 2013, for an overarching framework). Differences in lexical and sublexical features animate the debate around the Dual Route Cascaded model (Coltheart et al., 2001), postulating the existence of whole-word forms, against connectionist models (Plaut et al., 1996; Seidenberg, 2005), which propose a fully-sublexical locus of processing for the written input. A similar debate involves the role of morphological information: while morphemes (sublexical units that convey a fairly predictable form-to-meaning mapping, e.g., -*ness*) are widely considered to constitute an important part of the processing pathway toward visual word identification, models differ as to where these processing units might lie along this pathway (Crepaldi et al., 2010; Feldman & Basnight-Brown, 2008; Feldman et al., 2012; Taft, 2004; Taft & Nguyen-Hoan, 2010), and how they interact with other units (Grainger & Beyersmann, 2017; Grainger & Ziegler, 2011). In a strikingly close tandem, disentangling the role of lexical and sublexical information, along with other potentially relevant linguistic dimensions, is a fundamental step to steer both neural and cognitive debates, and significantly advance our understanding of skilled reading.

Substantial contributions in this direction came from neuroimaging studies using adaptation techniques. Neural habituation phenomena (such as repetition suppression and visual adaptation, Grill-Spector et al., 2006; Henson et al., 2004; Kohn, 2007) manifest the tendency of neural responses to decrease over time when the same stimulus – or stimulus feature, such as orientation, size or type – is repeated. Subsequently, neural habituation is considered to reflect the selectivity of neuronal populations to specific features, and is therefore uniquely suited to implicitly address discrimination processes. The careful variation of specific visual word properties probed neuronal tuning to abstract representations, leading to fMRI responses that were invariant to font, size, case and location (Dehaene et al., 2004; Dehaene et al., 2001). More recently, Lochy et al. (2015) obtained selective neural responses for lexical items by combining EEG recordings with oddball sequences – the so-called Fast Periodic Visual Stimulation paradigm (FPVS, Rossion, 2014). This technique adopts frequency tagging to isolate the brain's oscillatory response induced by the rapid, periodic presentation of visual items at a fixed rate (Norcia et al., 2015). Specifically, skilled readers were presented with periodic streams of stimuli (e.g., pseudowords, presented with a frequency of 10 Hz) in which word items appeared at regular intervals (every 5 items, hence with a 2 Hz frequency). Known words elicited a neural entrainment, as evidenced by a sharp 2 Hz response measured at scalp, reflecting the brain's ability to implicitly and rapidly discriminate lexical items in a stream of readable, ortho-phonotactically legal but non existing pseudowords.

A series of studies adopting linguistic material (e.g., Lochy et al., 2018; Lochy et al., 2015; Lochy et al., 2016) showcases the FPVS technique as a powerful window into the neural basis of visual word processing. Neural discrimination responses are elicited within few minutes of stimulation, are clearly quantifiable at the predefined frequency of interest, and yield high signal-to-noise ratios. Importantly, any response is gathered implicitly, in the absence of task-induced confounds, and is selective to the dimension that differentiates the two classes of items presented within the stimulation sequence. Accordingly, carefully controlled FPVS sequences could not only address the existence of lexical representations, but also probe the specific contributions of all the features that characterize linguistic information. Written input is indeed composed of a series of nested levels, with phonological, orthographic and semantic factors permeating different units of processing. In the eyes of a skilled reader, known words are highly familiar, complex visual objects, which become perceptually salient after a lifetime exposure (a mechanism akin to perceptual learning, Fahle et al., 2002; Gilbert et al., 2001; Goldstone, 1998; Nazir et al., 2004; Nazir & Huckauf, 2007). Structurally, visual words are combinations of known symbols (e.g., letters) that reflect the statistical co-occurrence regularities of the written language (Araújo et al., 2015; Lin et al., 2011; Rudell & Hu, 2000). Words have also consistent phonological (Aparicio et al., 2007; Braun et al., 2015; Dietz et al., 2005), morphological (Leminen et al., 2016; Leminen et al., 2013; Leminen et al., 2019; Vigliocco et al., 2006) and semantic associations (Devereux et al., 2013; Mirman & Magnuson, 2009; Price et al., 2006).

The present study aimed at investigating the contribution of each of these features by coupling MEG recordings with FPVS sequences, in a tightly controlled hierarchy of contrasts. Critically, each contrast tackled a specific linguistic feature, seeking evidence for its relevance in skilled reading. We assessed the presence of an Alphabetic response, by contrasting strings of consonants (e.g., *sfcl*) with sequences of items composed of artificial characters matching Roman letters on low-level visual features (BACS-2 characters, C. Vidal & Chetail, 2017). The same strings of consonants were then pitted against readable, but non-existing strings (e.g., *amsi*), to test the relevance of Readability. Readable items were then compared to meaningless word endings that are highly frequent in the written language (e.g., *enso*), to investigate the impact of Familiarity. Such frequent units were then set against suffixes, frequent and meaningful sublexical items (e.g., *eria*), so that we could directly investigate a Meaningfulness response. The final comparison involved suffixes on one hand, and words (e.g., *idea*) on the other: a successful discrimination, here, would represent a purely lexical response, in that both classes of items are frequently attested in the written environment and consistently associated with meaning, and are exclusively differentiated on the basis of their lexical status.

3.2 Materials and Methods

Participants

Twenty-one volunteers (10 females; age: M=27.2, SD=5.35) took part in the experiment after giving written informed consent. All participants were right-handed native Italian speakers reporting having normal or corrected-to-normal vision and no history of linguistic or neurological impairment. The experiment was conducted in accordance with the Declaration of Helsinki and was approved by the local ethical committee of the University of Trento.

Materials

Stimuli (illustrated in Figure 3.1) comprised six categories of 32 items, all three-to-four elements long (M=3.53, SD=0.507). Words (W, e.g., *idea*) were Italian nouns, and Suffixes (Suff, e.g., *eria*) were derivational morphemes. Frequent Endings (HFE, e.g., *enso*) were highly frequent, meaningless word endings attested in Italian. Pseudoendings (PE, e.g., *amsi*) were novel pronounceable letter strings with a regular CV-structure (i.e., fourteen items: CCV, seventeen items: VCCV, one item: VVV) that could constitute ortho-phonotactically legal word endings in Italian, but are not attested. Nonword stimuli (NW, e.g., *sfcl*) comprised random consonant strings and were thus unpronounceable. Finally, Pseudofont (PF) strings were obtained by rendering random combinations of characters from the BACS-2 serif artificial script (C. Vidal & Chetail, 2017), and resulted in strings of symbols closely matching the visual characteristics of Latin characters (i.e., number of strokes, junctions, terminations, and serifs).

Among the linguistic items, Words, Suffixes and Frequent Endings had a high and comparable written frequency (W: M=4.507, SD=0.580; Suff: M=4.983, SD=0.533; HFE: M=4.229; SD=0.925, as assessed SUBTLEX-IT, Crepaldi et al., 2013), while Pseudoendings and Nonwords had a zero frequency, as per their definition.

Procedure

Stimuli were presented via sinusoidal contrast modulation at a frequency of 6 Hz for 26.7 seconds, with each stimulus cycle lasting a total of 166.66 ms. Two types of stimulation sequences were presented for each condition. In experimental trials, the stimulation alternated between stimuli that belonged to two different categories (i.e., XYXYXYXY. . .), such that stimuli from each category were presented every 333.33 ms (i.e., at a frequency rate of 6 Hz/2=3 Hz). In baseline trials, a sequence comprised stimuli that belonged only to one category (i.e., XXXXXXXX. . .). This design ensured that in each experimental condition a differential signal (i.e., difference between alternating and baseline sequences) at the stimulation frequency of 3 Hz reflected a neural response that was selective to the property that distinguished the two categories of stimuli. For a schematic illustration of the experimental design and examples of stimulation sequences, see Figure 3.1.

Five experimental conditions were used to isolate neural responses to stimuli that are alphabetic (Nonwords vs. Pseudofonts; baseline: Nonwords), readable (Pseudoendings vs. Nonwords; baseline: Pseudoendings), sublexical orthographic units (Frequent Endings vs. Pseudoendings; baseline: Frequent Endings), sublexical meaningful units (Suffixes vs. Frequent Endings; baseline: Suffixes), and lexical units (Words vs. Suffixes; baseline: Words). There were 6 trials per experimental condition and type of sequence, yielding a total stimulation time of 45 minutes: 26.7 s (trial duration) x 5 experimental conditions x 2 types of sequences (alternating, baseline) x 6 trials. Trials consisted of unique sequences of 160 stimuli, each of which was presented exactly five times in a pseudo-randomized fashion to avoid close repetitions. The order of trial presentation was also pseudo-randomized to avoid close repetitions of specific classes of items during the course of the experimental session. Trial presentations were separated by 15-second breaks.

Participants were seated at approximately 1 meter from a PROPixx DLP projector (VPixx Technologies, Canada). The screen had a 1440x1080 pixels resolution and a refresh rate of 120 Hz. Stimulus display was administered by PsychToolbox-3 (Brainard, 1997) on MATLAB R2015a (The MathWorks)

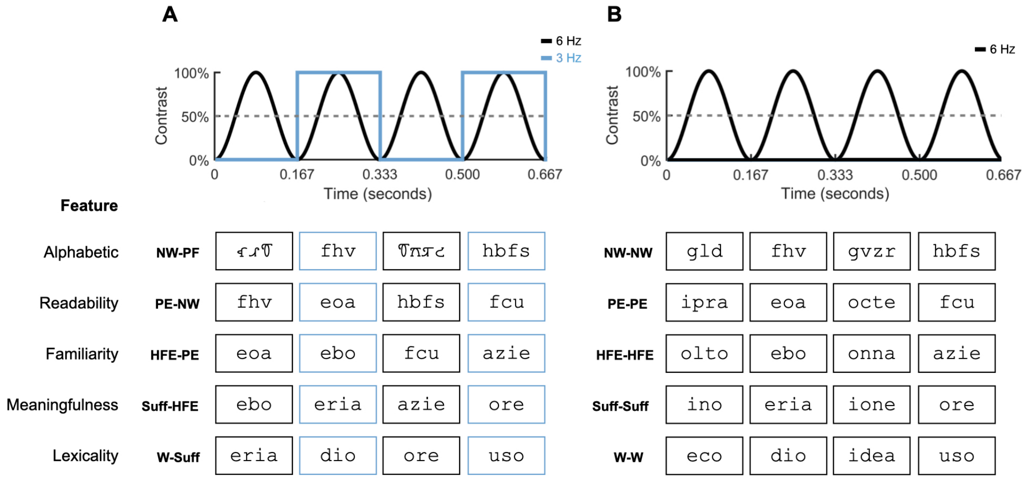


Figure 3.1: Experimental Paradigm. All stimuli were presented by sinusoidal contrast modulation; the figure displays four cycles of 166.66 ms. In the experimental trials (panel A) stimuli from two classes were alternated, to isolate neural responses selective to discriminative properties (e.g., letter strings and pseudo-characters differ solely on the basis of their alphabetic nature). Examples are given for the five different properties of interest: Alphabetic (Nonwords, NW, vs. Pseudofonts, PF), Readability (Pseudoendings, PE, vs. Nonwords, NW), Familiarity (High frequency endings, HFE, vs. Pseudoendings, PE), Meaningfulness (High frequency endings, HFE, vs. Suffixes, Suff), and Lexicality (Words, W, vs. Suffixes, Suff). The control trials (panel B) comprised items belonging to the same category (e.g., a single stream of letter strings), and served as a baseline for the discriminative nature of the neural responses yielded by the experimental trials. Particularly, the difference between the 3 Hz response in experimental and baseline trials would represent a genuine discrimination between items belonging to two different experimental categories, thus reflecting the feature under study.

in a Windows environment. All stimuli were presented at the center of the screen. All alphabetic stimuli (i.e., Words, Suffixes, Frequent Endings, Pseudoendings and Nonwords) were presented in lowercase characters, using the fixed-width Courier New font, whereas Pseudofonts were presented in BACS-2 serif font. Both fonts were emboldened by 70% from their original character weight to improve visibility. Each stimulus subtended horizontal and vertical visual angles of 2.58 and 0.64 degrees, respectively.

To ensure participants maintained a constant level of attention, they were instructed to monitor the color change of a cross presented continuously at the center of the screen. The change, from blue to red and vice versa, occurred three times in each trial, independently of the experimental manipulation. Overall, participants' performance in the color-change detection task was close to ceiling in accuracy (M=97.8%, SD=14), and featured fast reaction times, (M=465 ms, SD=177). Moreover, it was comparable across experimental trials (NW in PF=97%, SD=16, reaction time: M=460 ms, SD=157; PE in NW=97.3%, SD=16, reaction time: M=469 ms, SD=188; HFE in PE=98.4%, SD=12, reaction time: M=468 ms, SD=175; Suff in HFE=97.8%, SD=14, reaction time: M=476 ms, SD=202; W in Suff=98.6%, SD=11, reaction time: M=452, SD=145) as well as baseline trials (NW in NW=97.3%, SD=16, reaction time: M=466 ms, SD=189; PE in PE=98.1%, SD=13, reaction time: M=455 ms, SD=149; HFE in HFE=97.8%, SD=14, reaction time: M=477 ms, SD=216; Suff in Suff=97.6%, SD=15, reaction time: M=461 ms, SD=160; W in W=98.4%, SD=12, reaction time: M=462 ms, SD=173).

MEG acquisition, Preprocessing and Frequency analysis

MEG data were recorded using a whole-head 306 sensor (204 planar gradiometers; 102 magnetometers) Vector-view system (Elekta Neuromag, Helsinki, Finland). Participants' head position was continuously determined with respect to the MEG helmet through five head position indicator coils (HPIs). MEG signals were recorded at a sampling rate of 1000 Hz and online band-pass filtered between 0.1 and 300 Hz. At the beginning of each experimental session, fiducial points of the head (the nasion and the left and right pre-auricular points) and a minimum of 300 other head-shape samples were digitized using a Polhemus FASTRAK 3D 519 digitizer (Fastrak Polhemus, Inc., Colchester, VA, USA).

Raw data were processed through MaxFilter 2.0 (Elekta Neuromag). For each participant, bad channels were identified via visual inspection, and interpolated. Head displacements were inspected and corrected through realignment to a single reference. After applying movement compensation, external sources of noise were separated and removed by applying the temporal extension of signal space separation (tSSS; Medvedovsky et al., 2009; Taulu and Hari, 2009; Taulu and Simola, 2006).

Preprocessing and analysis were performed in MATLAB (MathWorks, Inc) with a combination of Fieldtrip (Oostenveld et al., 2011), Brainstorm (Tadel et al., 2011) and custom scripts. Continuous recordings from each participant were band-pass filtered (0.1 - 100 Hz), downsampled (250 Hz) and epoched into 26.7-seconds trials, which were realigned to the onset of the first stimulus (via photodiode). Segments contaminated by artifacts were identified through visual inspection and manually removed (1.11%). To remove eye movements and heartbeat related artifacts from the MEG signal we performed an Independent Component Analysis (ICA, Jutten & Herault, 1991), separately for magnetometers and planar gradiometers. Eye movement and pulse-related components were captured by correlating the independent component (IC) time series with that of EOG and ECG channels. For each participant, trials within each condition were averaged, and submitted to a Fast Fourier Transform. Given the length of the epochs, the frequency resolution was 1/26.7=0.0374 Hz. The spectra were then baseline-corrected by subtracting from each frequency bin the mean of the surrounding 20 bins (10 from each side, excluding local minima, maxima and immediately adjacent bins, as in e.g., Dzhelyova and Rossion, 2014); the response of interest was then defined as the baseline-corrected amplitude 3 Hz. A significant discrimination response, indexing neural entrainments elicited by items belonging to different categories, was assessed by comparing the 3 Hz response in each experimental condition (e.g., Words in Suffixes) with the corresponding baseline (i.e., Words in Words).

Sensor Space Analysis Sensor level analyses were run at whole-brain level through a non-parametric cluster permutation test (Maris & Oostenveld, 2007). Differences at 3 Hz for both experimental and baseline conditions were assessed separately for magnetometers and combined planar gradiometers, by considering a minimum neighborhood distance of 6 millimeters between sensors. Statistical significance was assessed through a one-tail, dependent sample t-test with Monte-Carlo estimates over 5000 permutations (significance level: $p<0.05$).

Source Space Analysis Distributed minimum-norm source estimation (MNE, Hämäläinen & Ilmoniemi, 1994) was applied following the standard procedure in Brainstorm (Tadel et al., 2011). For twenty participants, anatomical T1-weighted MRI images were acquired during a separate session in a Prisma 3T scanner (Siemens, Erlangen, Germany) using a 3D MPRAGE sequence, 1-mm3 resolution, TR=2140 ms, TI=900ms, TE=2.9ms, flip angle 12°, and segmented in Freesurfer (Fischl, 2012). Co-registration of MEG sensor configuration and the reconstructed scalp surfaces was based on around 300 scalp surface locations. As one participant did not undergo MRI acquisition, we warped the default anatomy to match the shape defined by the digitized points. Individual noise covariance matrices were computed from 1 s pre-stimulus interval in all the available trials for each participant. The forward model was obtained using the overlapping spheres method (Huang et al., 1999) as implemented in Brainstorm. Fourier-transformed regression coefficients were then projected onto a 15000 vertices boundary element using a dynamic statistical parametric mapping approach (dSPM; Dale et al., 2000), assuming dipole sources to be perpendicular to the cortical surface. Individual results were spatially smoothed (3mm FWHM) and projected to a default template (ICBM152).

Differences at 3 Hz between experimental and baseline conditions were then assessed at source level in the vertices of predefined regions of interest, obtained from the Desikan-Killiany cortical atlas (Desikan et al., 2006). ROIs corresponded to several cortices involved in reading, such as fusiform (e.g., Dehaene et al., 2002), lingual (e.g., Raschle et al., 2011), inferior parietal (e.g., Sliwinska et al., 2015), inferior temporal (e.g., Dien et al., 2013), lateral occipital (e.g., Borowsky et al., 2007) and middle temporal (e.g., Turkeltaub et al., 2003). On each ROI, significant responses were assessed via nonparametric cluster permutation test (N=5000, p<0.05; Maris & Oostenveld, 2007). Non-significant effects were here explored through JZS Bayes Factor analysis (BF_{10}, scale factor r=0.707; Rouder et al., 2009), which provides quantifiable evidence in support of H1 or H0, thus allowing to support the null hypothesis itself (Leppink et al., 2017).

3.3 Results

Sensor Space As shown in Figure 3.2, clear discrimination response indicated sensitivity to alphabetic items (NW-PF vs. NW-NW), emerging in a diffused area for both planar gradiometers ($t_{(20)}$=311.13, p=0.0002, g=0.83 [95% CI: 0.53, 1.13]) and magnetometers ($t_{(20)}$=274.17, p=0.0002, g=0.81 [95% CI: 0.49, 1.12]). Lexical items embedded in suffixes (W-Suff vs. W-W) also elicited a marked discrimination response, with left-lateralized topography for both planar gradiometers ($t_{(20)}$=80.30, p=0.0004, g=0.65 [95% CI: 0.12, 1.16]) and magnetometers ($t_{(20)}$=74.28, p=0.0002, g=0.71 [95% CI: 0.18, 1.22]).

No discrimination response emerged as statistically significant for the other contrasts. Readability (PE-NW vs. PE-PE) resulted in a cluster that did not reach significance in planar gradiometers ($t_{(20)}$=9.39, p=0.13, g=0.61 [95% CI: -0.91, 2.01]) and no cluster for magnetometers; Familiarity (HFE-PE vs. HFE-HFE), produced a non-significant cluster for magnetometers ($t_{(20)}$=8.81, p=0.233, g=1.03 [95% CI: -0.93, 3]) and no cluster for gradiometers. No significant cluster emerged for meaningful sublexical units (Suff-HFE vs. Suff-Suff).

Source Space Significant discrimination responses in the predefined ROIs are displayed in Figure 3.3. At source level, a 3 Hz discrimination response for alphabetic stimuli (NW-PF vs. NW-NW) emerged bilaterally in all the areas of interest (as summarized in Table 3.1).

A discrimination of readable stimuli in strings of consonants (PE-NW vs. PE-PE) yielded a right-lateralized profile, involving fusiform ($t_{(20)}$=161.31, p=0.0216, g=1.23 [95% CI: 0.82, 1.63]), inferotemporal ($t_{(20)}$=134.31, p=0.0206, g=1.30 [95% CI: 0.86, 1.72]), lateral occipital ($t_{(20)}$=204.39, p=0.024, g=1.16

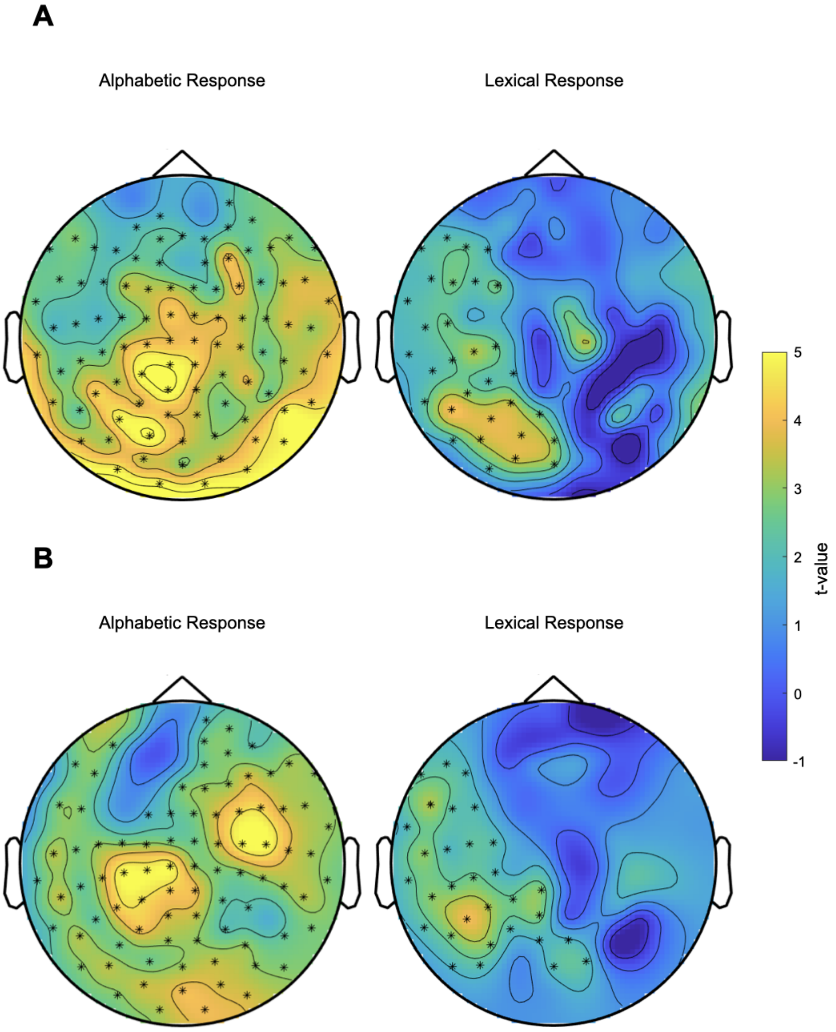


Figure 3.2: Sensor level results. One significant, largely diffused cluster indicated the discrimination of alphabetic stimuli, while a left-lateralized significant cluster was associated with lexical discrimination. The topography of the effects is comparable across planar gradiometers (panel A) and magnetometers (panel B) for both discrimination responses.

ROI	**t value**	**Effect size *g***	**Pr(>| *t* |)**	
Left Fusiform	1059.21	1.57 [1.36, 1.77]	<0.001	***
Right Fusiform	956.08	1.91 [1.69, 2.12]	<0.001	***
Left Inferiorparietal	1060.81	1.35 [1.18, 1.52]	<0.001	***
Right Inferiorparietal	1315.81	1.37 [1.22, 1.52]	<0.001	***
Left Inferotemporal	903.83	1.29 [1.10, 1.48]	<0.001	***
Right Inferotemporal	1052.57	1.57 [1.38, 1.75]	<0.001	***
Left Lateral Occipital	1609.02	1.48 [1.32, 1.65]	<0.001	***
Right Lateral Occipital	1313.58	1.62 [1.45, 1.79]	<0.001	***
Left Lingual	921.25	1.59 [1.37, 1.80]	<0.001	***
Right Lingual	729.36	1.70 [1.47, 1.92]	<0.001	***
Left Middle temporal	603.84	1.03 [0.82, 1.25]	<0.001	***
Right Middle temporal	1141.24	1.38 [1.20, 1.55]	<0.001	***

Table 3.1: Alphabetic Response (PF-NW vs. NW-NW), Source Level Results.

[95% CI: 0.82, 1.49]) and middle temporal cortices ($t_{(20)}$=105.35, p=0.0332, g=0.92 [95% CI: 0.48, 1.34]).

Familiarity (HFE-PE vs. HFE-HFE) elicited significant responses only in the right inferior temporal area ($t_{(20)}$=220.03, p=0.0178, g=1.14 [95% CI: 0.81, 1.47]). Consistently with the results observed in sensor space, suffixes embedded in frequent endings (Suff-HFE vs. Suff-Suff) yielded no significant response in the predefined ROIs. This null result was further explored through a JZS Bayes Factor analysis across ROIs, which, where conclusive, provided moderate evidence in favor of the null hypothesis (as summarized in Table 3.2).

Differences between words and suffixes (W-Suff vs. W-W) were traced in bilateral fusiform (left: $t_{(20)}$=227.12, p=0.0174, g=1.11 [95% CI: 0.77, 1.44]; right: $t_{(20)}$=283.35, p=0.004, g=0.94 [95% CI: 0.65, 1.22]), together with two significant clusters in left inferior temporal (first: $t_{(20)}$=230.97, p=0.0206,

ROI	**Number of Vertices**	**BF_{10}<1/3**	**BF_{10}>3**
Left Fusiform	268	156 (58%)	0
Right Fusiform	255	186 (72%)	0
Left Inferiorparietal	351	70 (19%)	39 (11%)
Right Inferiorparietal	421	219 (52%)	20 (5%)
Left Inferotemporal	307	155 (50%)	0
Right Inferotemporal	316	213 (67%)	9 (3%)
Left Lateral Occipital	371	207 (55%)	4 (1%)
Right Lateral Occipital	367	251 (68%)	0
Left Lingual	246	154 (62%)	0
Right Lingual	227	186 (82%)	0
Left Middle temporal	277	191 (69%)	9 (3%)
Right Middle temporal	324	205 (63%)	19 (6%)

Table 3.2: Suff-HFE vs. Suff-Suff contrast, Source Level Bayes Factor Analysis. For each ROI, the table reports the total number of vertices, the ones providing moderate evidence in favor of the Null hypothesis (i.e., with $BF_{10}<1/3$) and those moderately supporting the alternative (i.e., with $BF_{10}>3$).

g=1.01 [95% CI: 0.68, 1.33]; second: $t_{(20)}$=186.03, p=0.029, g=0.93 [95% CI: 0.55, 1.29]), left lateral occipital ($t_{(20)}$=580.00, p=0.0008, g=0.77 [95% CI: 0.57, 0.97]) and left lingual ($t_{(20)}$=436.91, p=0.004, g=1.23 [95% CI: 0.98, 1.48]).

3.4 Discussion

The present study investigated the neural underpinnings of skilled reading, by asking which linguistic features might be rapidly and automatically discriminated by the reading brain. With this aim, we paired MEG record-

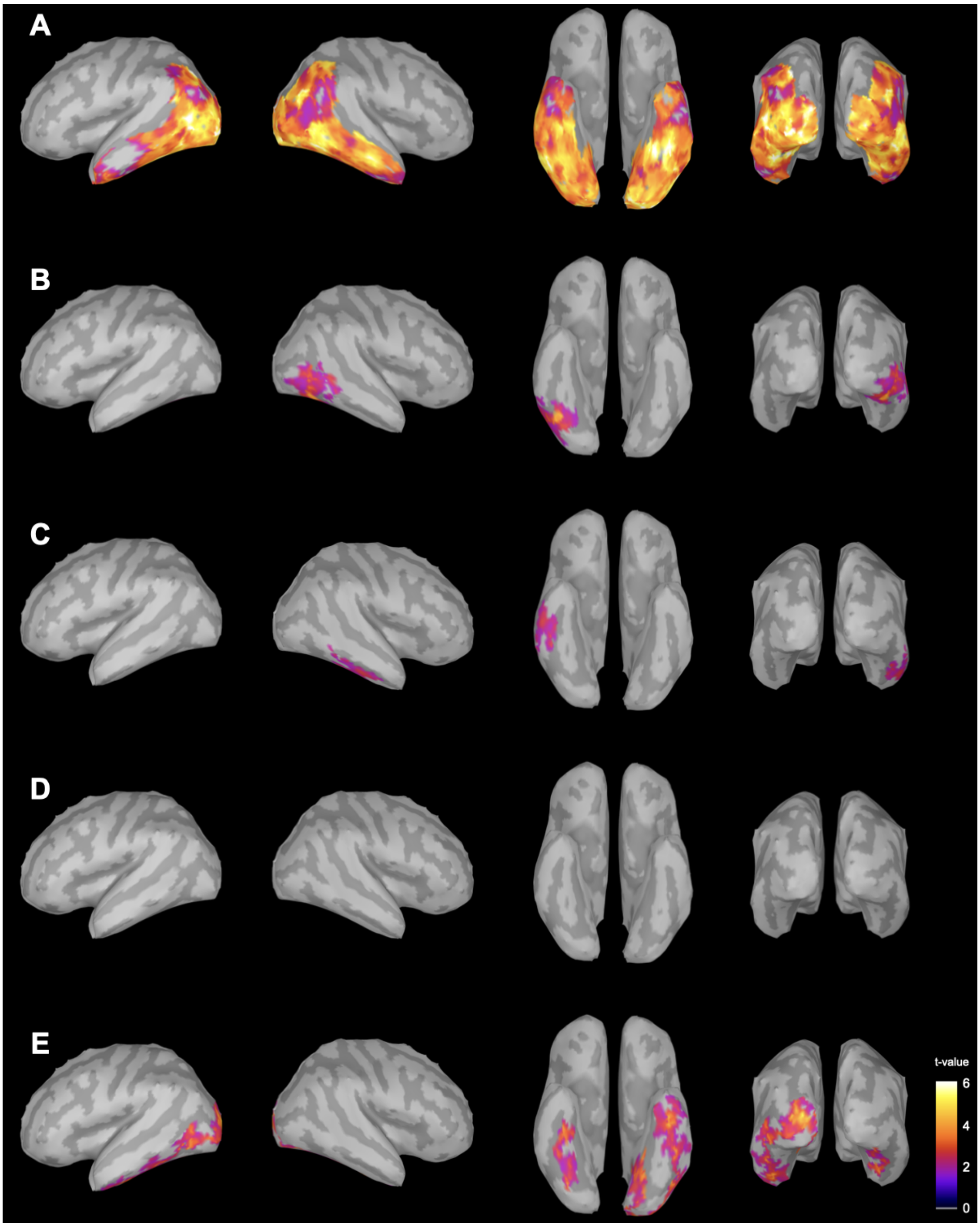


Figure 3.3: Source level results. Significant discrimination responses ($p<0.05$) for the five linguistic properties under study (from the top: (A) Alphabetic, (B) Readability, (C) Familiarity, (D) Meaningfulness, (E) Lexicality), displayed (from left to right) with left, right, ventral and posterior views.

ings with Fast Periodic Visual Stimulation sequences (FPVS, Rossion, 2014) constructed specifically to isolate some fundamental features of written text, in a carefully controlled hierarchy of nested contrasts. In this design, observing a neural entertainment at the frequency with which classes of items were presented implicitly indexes a selective discrimination for the feature that differentiates the two groups of items. Interleaving words (e.g., *idea*) and suffixes (e.g., *eria*) revealed a strong Lexicality response, already detectable at sensor level. Similarly, the alternation of pseudo-characters and letter strings (e.g., *sfcl*) revealed a strong sensitivity to the alphabetic nature of the stimuli, also observable at both sensor and source levels. More subtle contrasts, addressing the role of Readability (with strings of consonants, e.g., *sfcl* vs. pseudoendings, e.g., *ampi*) and Familiarity of letter strings (with high frequency endings, e.g., *enso* vs. pseudoendings, e.g., *ampi*), were captured only at source level. Notably, our results did not reveal a Meaningfulness response, as assessed by contrasting suffixes (e.g., *eria*) with equally frequent, but meaningless word endings (i.e., *enso*).

The reading system is automatically responsive to rapidly presented lexical items, suggesting a marked neural sensitivity to whole words. Such response is characterized by a predominantly left-lateralized profile, arising in areas typically associated with word identification and processing, such as left lateral occipital, lingual and inferotemporal cortices (J. Binder & Price, 2001; Borowsky et al., 2007), as well as the bilateral fusiform gyrus (Cohen et al., 2002; Dehaene et al., 2002; Fiez & Petersen, 1998; Puce et al., 1996). This selective neural discrimination for word forms speaks to the cognitive debate around lexicality, and lends some support to the existence of an orthographic lexicon, consistently with more recent neural models of reading (Taylor et al., 2013). Nevertheless, the spatial resolution of non-invasive human neuroimaging in general, and of MEG in particular, requires a word of caution in interpreting this result. Specifically, our findings cannot pinpoint whether this Lexical response originates from a set of individual neurons specifically selective to words *per se*, or rather from a coordinated, large ensemble of neurons with a less granular preference. Therefore, the present study cannot arbitrate between localist and distributed accounts of lexical neural codes at a mechanistic level (Bowers, 2009, 2017; Quian Quiroga & Kreiman, 2010; Roy, 2012; Vankov & Bowers, 2017).

Neuroimaging evidence has been fairly elusive as to whether the reading brain responds specifically to existing words (as opposed to well formed strings of letters, e.g., J. R. Binder et al., 2006; Dehaene et al., 2005; Pammer et al., 2004; Price et al., 1996; Wydell et al., 2003). The adoption of neural adaptation techniques has provided a decisive methodological boost in this direction, by allowing to tap into selective neuronal tunings to stimulus features (Grill-Spector et al., 2006; Norcia et al., 2015). Importantly however, while previous studies succeeded in capturing selective adaptation to lexical forms (e.g., Glezer et al., 2009; Lochy et al., 2015), they generally did so by pitting words against pseudowords, thus adopting two classes of items that differ on more than one relevant dimension. Written words are indeed meaningful linguistic objects, with a known phonological and orthographic form, while well-structured pseudowords are, albeit pronounceable (Taylor et al., 2013), unknown strings of letters. Contrariwise, the Lexical response obtained in the present study stems from an unprecedentedly tight comparison, realized by contrasting fully-fledged, real words with suffixes. Morphemes like -*ness* or -*er* are attested in the language with high frequency, and due to their derivational properties, they alter the meaning of stems they are combined with in a highly predictable and consistent manner (e.g., kind*ness*, high*ness*, sing*er*, danc*er*), thus have a specific meaning (Bloomfield, 1933; Bybee, 1988). Similar to words, suffixes forge strong and consistent associations between their orthographic form and a semantic concept (e.g., the suffix -*er* conveys agency, while -*ness* denotes quality, condition or state), and they only differ from words in their sublexical, rather than lexical, status, in that they cannot appear in isolation, as independent linguistic units. Therefore, the adoption of morphemes allows to uniquely overcome the rather coarse characterization of the lexical discrimination obtained with pseudowords, and supports the presence of a neural response that is specifically lexical, not related to meaning, frequency of occurrence or readability alone.

Indubitably, sublexical morphemes such as suffixes play a fundamental function in visual word identification. Behavioral evidence has extensively supported the role of morphemes in the recognition of complex words (as reviewed in, e.g., Amenta & Crepaldi, 2012; Giraudo & Voga, 2014; Rastle & Davis, 2008), which was further corroborated by several neuroimaging studies (e.g., Beyersmann et al., 2021; M. H. Davis et al., 2004; Devlin et al., 2004; Gold and Rastle, 2007; Lavric et al., 2012; Lehtonen et al., 2011; Lewis et al., 2011; for a recent review, see Leminen et al., 2019). Nevertheless, the vast majority of the available studies investigated the role of morphemes by embedding them in a lexical context (i.e., morphologically complex words, e.g., *kind-ness*, or pseudowords, e.g., *table-ness*), and thus leaves their specific neural characterization somewhat underspecified. The present study provides novel insights by showing that, when presented in isolation, suffixes are not reliably distinguished from frequent word endings. Such finding nicely reckons with recent experimental evidence obtained in artificial lexicon studies indicating that skilled readers can carve affix-like units on the sole basis of their frequency of occurrence, and in the absence of phonological or semantic information (e.g., Chetail, 2017; Lelonkiewicz et al., 2020). Collectively, this body of evidence does not abide by cognitive models of morphological processing that assume dedicated representations for meaningful, sublexical units (e.g., Crepaldi et al., 2010; Taft, 2004; Taft & Nguyen-Hoan, 2010), and is better aligned with accounts emphasizing perceptual and orthographic mechanisms for the decomposition of complex words (e.g., Grainger & Beyersmann, 2017). Particularly, Grainger and Beyersmann (2017) theorize that while the recognition of sublexical units is achieved on the basis of orthographic factors, their semantic activation is primarily driven by the lexical context in which they appear (e.g., the meaning of *-er* would be activated when the suffix is presented in an adequate context, like *sing-er*). Coherently, and in spite of their morphological status, isolated suffixes would be no more perceptually salient than other highly frequent word endings.

Taken together, our results are likely to reflect the sensitivity of the reading system to form-based regularities, by tapping into the bottom-up processing of visuo-linguistic material. Words stood out as independent units even if compared with another set of meaning-bearing items, consistently with theories of perceptual learning (Fahle et al., 2002; Gilbert et al., 2001; Goldstone, 1998). The lexical knowledge available to skilled readers is indeed not only reliant on linguistic information, but also on the visual familiarity that results from an extensive experience with written text, where frequent and repeated encounters with printed words would consolidate their representation as complex but unitary shapes, rather than combination of features (Gilbert et al., 2001; Kennedy et al., 2000; Nazir & Huckauf, 2007). Consequently, individual words would become privileged units of processing that “pop-out” (Nazir et al., 2004) to the eyes of a skilled reader, particularly if displayed in their most prototypical form (as, for instance, in a horizontal orientation, Nazir &

Huckauf, 2007; Wimmer et al., 2016). Critically, word tokens are generally surrounded by empty spaces, which provide privileged anchor points to infer letter information and, subsequently, word identity (Fischer-Baum et al., 2011; Grainger & Beyersmann, 2017; Jacobs et al., 2013). Such perceptual salience might not be comparably bestowed upon suffixes, which, although frequent and meaningful, are bound to appear within complex words and are never encountered independently. Coherently, bound morphemes like suffixes were not significantly discriminated by highly frequent, but meaningless word endings, as both classes of items are comparably familiar in their form and are equally supported by the perceptual experience of skilled readers.

The selective neural responses for Alphabetic stimuli, as well as for Readability and Familiarity, also sit well with a bottom-up account of the present results. Strings of consonants embedded in pseudo-characters elicited a strong and diffused response, involving all the predefined regions of interest considered. Such a pervasive Alphabetic response suggests that, despite pseudo-characters being carefully matched onto letters' low-level visual features (C. Vidal & Chetail, 2017), letter-based configurations were markedly more familiar to skilled readers (Lochy et al., 2018; Lochy et al., 2015; Lochy et al., 2016; Thesen et al., 2012; van de Walle de Ghelcke et al., 2020; Vinckier et al., 2007; Wang et al., 2021). When contrasted with strings of consonants, readable but non-attested sequences of letters (e.g., *ampi*) elicited a right-lateralized response encompassing fusiform, lateral occipital and both middle and inferior temporal ROIs, areas reportedly involved in vowel processing, as opposed to consonants (Carreiras & Price, 2008; Carreiras et al., 2009) and non-speech (Obleser et al., 2006; Uppenkamp et al., 2006). Critically, ortho-phonotactically legal items are not only readable, but also more word-like (as opposed to consonant strings), a feature considered to be at the core of the neural underpinnings of reading (e.g., J. R. Binder et al., 2006; Vinckier et al., 2007), and consistent with a form-based regularity account of the present findings. In a transparent orthography like Italian, orthographic units are unambiguously associated with a phonological pattern, thus hampering a clear-cut distinction between the effects of familiarity and readability *per se*. Nevertheless, recent neuroimaging evidence obtained in Hebrew (Weiss et al., 2015) seems to support a privileged role for familiarity over orthographic transparency. By exposing skilled readers to words with vowel sounds rendered either through vowels alone, or with the adoption of diacritic markers, Weiss et al. (2015) observed that the more familiar format (i.e., without diacritics) provided a major processing advantage. This advantage overrode the increased transparency ensured by the presence of diacritics, hence pinpointing visual familiarity as a key feature in the neural processing of readable stimuli (see, e.g., Chetail & Boursain, 2019; Kinoshita et al., 2021; Marcet et al., 2020; Perea et al., 2020; Perea et al., 2022, for recent behavioral investigations on the topic).

Finally, the contrast between readable but non-existing word endings (e.g., *ampi*) and highly frequent word endings (e.g., *enso*) resulted in a selective neural entrainment sourced in an anterior portion of the right inferotemporal ROI. Behavioral research on reading pullulates with effects of written frequency, which have been often considered proxies of learned representations (Baayen et al., 2007; Burani and Thornton, 2003; Colé et al., 1989; Monsell et al., 1989; Preston, 1935; Taft, 1979, 2004; see, e.g., Brysbaert et al., 2018; Ellis, 2002 for reviews). Neuroimaging studies indicate that frequency effects can be traced throughout several visual word identification processes (Barber & Kutas, 2007), and that frequency-modulated activations might be housed in occipitotemporal regions (e.g., S. J. Frost et al., 2005; Keller et al., 2001; Kuo et al., 2003; Montani et al., 2019; Vinckier et al., 2007; but see, e.g., Fiebach et al., 2002; Fiez et al., 1999; Ischebeck et al., 2004 for diverging patterns of results). Notably, written frequency effects are reminiscent of a more general recognition mechanism of extraction and storage of recurring patterns, including words, faces and other salient visual objects (Kronbichler et al., 2004; Y. Vidal et al., 2021). In keeping with this conjecture, the selective neural entrainment elicited by high-frequency clusters in the present study stems from a portion of the inferior temporal cortex, which constitutes a cornerstone of visual object encoding (DiCarlo et al., 2012). Particularly, this area has been attested to support the processing of orthographic items in primates (Rajalingham et al., 2020), and qualifies as a powerful visual processing resource to be recycled (Dehaene & Cohen, 2007) by the more phylogenetically recent reading system.

The bottom-up nature of the processes underpinning the present results is also supported by a series of methodological considerations. The FPVS technique allows to detect automatic and implicit neural discrimination responses within few minutes of stimulation, by capitalizing on a rapid presentation rate and lack of explicit engagement with the material (Liu-Shuang et al., 2014; Norcia et al., 2015; Rossion, 2014). Critically, stimuli are presented via sinusoidal contrast modulation (from white background to full contrast and back) with a frequency of 6 Hz, thus each item remains on screen for about 167 ms, reaching full contrast at 83 seconds, and with an actual visibility duration of around 140 ms (considering that stimuli can be recognized at low contrast levels, such as 20%, Lochy et al., 2015; Lochy et al., 2016). Such a brief presentation is complemented with the perceptual masking induced by sequential stimulus presentation, which unfolds without any inter-stimulus interval (in line with RSVP paradigms; see Retter et al., 2018, for a related discussion).

As a result, the present FPVS design is likely to tap into rather early stages of processing, which are probably informed more by bottom-up, visual and orthographic information rather than by top-down, higher level information (such as semantics).

Remarkably, the demanding nature of the stimulation stream is also consistent with the spatial profile of the more subtle responses obtained along the hierarchy of contrasts. Indeed, while linguistic processes are generally associated with activity in the left hemisphere (Dehaene et al., 2001; Pinel & Dehaene, 2010), the right hemisphere is reportedly more resilient to fast and degraded visual presentations of alphanumeric stimuli (e.g., Asanowicz et al., 2017; Hellige & Michimata, 1989; Jonsson & Hellige, 1986; Michimata & Hellige, 1987; Sergent & Hellige, 1986; Verleger et al., 2013; Verleger et al., 2011). Coherently, while a selective Lexical response resulted in a prototypical left-lateralized profile, more subtle, sublexical units could enjoy weaker support from pre-existent linguistic representations, which allowed the right-lateralized, perceptual response to be more easily captured. Future research is needed to address the impact of different experimental parameters, by systematically tuning the stimulation frequency to the feature of interest, and assessing whether different presentation rates could further qualify the neural entrainment hereby observed (for a related discussion, see Alonso-Prieto et al., 2013; Rossion, 2014).

In conclusion, the present study capitalized on FPVS and MEG recordings to shed some new light on which linguistic features underpin reading. Implicit discrimination responses emerged in a tightly controlled hierarchy of contrasts, whose extremes revealed a strong sensitivity to letters and lexical items. Sensitivity to the intermediate layers – the mere association with meaning, familiarity and readability – was generally weaker, if present at all. Taken together, these results provide novel insight into the brain's sensitivity to form-based regularities, and highlight the relevance of perceptual familiarity at the early stages of visual word identification.

Chapter 4

Study III: Frequency-based Neural Discrimination in Fast Periodic Visual Stimulation*

The human brain can learn implicitly and effortlessly from the statistical properties of an input stream. Known as implicit statistical learning, this remarkable, domain-general ability helps us make sense of the highly complex and ever-flowing sensory environment to which we are exposed, by enabling us to discover fundamental units of information (for recent reviews, see Armstrong et al., 2017; Aslin, 2017; Christiansen, 2019; R. Frost et al., 2019; E. L. Newport, 2016). Arguably, the most familiar experimental demonstrations of such a phenomenon come from language research, attesting our ability to detect conditional relations between elements in the input. For example, guided only by differences in the transitional probabilities (TPs) between syllables, we can extract out of a continuous stream of sounds multi-syllabic units that correspond to words, and differentiate them from nonwords (Saffran et al., 1996; for analogous findings in the visual modality with shapes, see Kirkham et al., 2002; Siegelman and Frost, 2015; Turk-Browne et al., 2005). In addition

---

*From De Rosa, M., Ktori, M., Vidal, Y., Bottini, R., & Crepaldi, D. (2022). *Frequency-Based Neural Discrimination in Fast Periodic Visual Stimulation.* Manuscript accepted for publication in *Cortex.*

to these, however, there are a host of statistical relations that can influence learning (Thiessen et al., 2013). By relying on the frequency distributions of phonemes in the input, for example, we are able to discover categorical prototypes (and boundaries), and distinguish between different phonemic categories (Maye et al., 2002; for analogous findings in the visual modality with low-level stimuli, see Rosenthal et al., 2001). In the current study, we examine whether distributional information can elicit implicit statistical learning in the context of an increasingly popular methodology that combines electrophysiological recording with Fast Periodic Visual Stimulation (FPVS).

Capitalizing on the principle of neural entrainment (for a review, see Norcia et al., 2015), the FPVS approach uses frequency tagging to effectively capture visual discrimination processes at the level of the brain (Rossion, 2014). In particular, this involves presenting sequences of base stimuli (i.e., a set of visual items) at a fast periodic frequency rate F interleaved with oddball stimuli (i.e., a set of items that differ from base stimuli on a dimension of interest), inserted at fixed intervals (every n item) and thus appearing at a slower periodic rate (F/n). A few minutes of stimulation are sufficient to evoke robust neural responses (i.e., steady state visual evoked potentials, SSVEP; Regan, 1966) that are clearly and objectively identifiable at the predefined base and oddball stimulation frequencies and their harmonics. Critically, the presence of a neural response at the oddball frequency reflects the brain's ability to discriminate between oddballs and base stimuli and is selective to the dimension that differentiates them. Finally, this neural discrimination response is obtained implicitly in the absence of task-induced measures, and it is thus devoid of potential contamination from other cognitive and decisional processes.

This highly sensitive and behavior-free approach has become particularly popular for probing category-selective processing at the level of perception (see also Coll et al., 2019; Stothart et al., 2017; Van der Donck et al., 2020, for higher-level categorization in emotion and semantic processing) and has provided important insights into the neural representation of stimuli such as faces, objects, and words, in studies with healthy adults (Jacques et al., 2016; Liu-Shuang et al., 2014; Lochy et al., 2015; Retter & Rossion, 2016; Rossion et al., 2015; Stacchi et al., 2019) and children (Lochy et al., 2016), as well as clinical populations (Liu-Shuang et al., 2016; Lochy et al., 2018; Stothart & Smith, 2020).

Beyond pre-established categorical differences, however, an important and outstanding question is whether this approach can also capture the emergence of a novel distinction. The FPVS-oddball design provides a context that can easily foster implicit statistical learning. Extensively used to explore the neural mechanisms that underlie the detection of novelty in our perceptual environment (i.e., mismatch negativity; for reviews see Kimura et al., 2011; Näätänen et al., 2007; Stefanics et al., 2014), the oddball paradigm features oddballs as rare deviants in a stream of frequent, standard events. A typical 60-second FPVS sequence, for example, with a base presentation rate of 6 Hz and an oddball embedded periodically every 5th item (i.e., $6/5 = 1.2$ Hz), comprises a total of 360 stimuli, out of which 288 are base stimuli and only 72 appear as oddballs. Differences in the frequency with which oddball and base stimuli occur in a given input stream are therefore inherent in the nature of the experimental paradigm. Importantly, this relative frequency-of-occurrence difference constitutes a source of distributional information on the basis of which oddballs (i.e., a group of infrequent stimuli) could be differentiated from base stimuli (i.e., a group of frequent stimuli), independently (or in the absence) of any pre-existing difference between them. But is the brain capable of such fast and implicit statistical learning simply based on the frequency-of-occurrence of perceptual events? And if so, is this frequency difference sufficient to elicit a neural discrimination response? To address these questions, we adopted a simple modification of the classic FPVS-oddball paradigm by exposing participants to homogeneous streams of stimuli, insofar all the items were drawn from the same category (e.g., word oddballs embedded in a sequence of words). Crucially, base and oddball types could be differentiated only by their respective frequency-of-occurrence within a presentation stream: oddball tokens appeared four times less often than base tokens (see Figure 1). Item assignment to oddball and base stimuli was performed randomly across participants who were engaged in an orthogonal task. Under these conditions and in the absence of other pre-existing or systematic distinctions between base and oddball stimuli, neural entrainment at the oddball stimulation frequency would index a selective discrimination response between two newly emerged groups of stimuli, generated purely on the basis of the statistical structure of the input stream.

In order to determine whether or not the emergence of such differential signal stems from a primary learning mechanism that applies to any perceptual event, participants were exposed to four types of linguistic stimuli: (1) familiar words (e.g., *pasta*); (2) pronounceable letter strings that are not attested as words in the lexicon (Pseudowords, e.g., *stapa*); (3) unpronounceable consonant strings (Nonwords, e.g., *qnlvd*), and (4) strings of letter-like, non–alphabetic characters (Pseudofonts; see Figure 4.1 for examples). We hypothesized that if sensitivity to local token frequency in the context of FPVS-oddball designs is influenced by stimulus familiarity, then discrimination responses would be modulated as stimuli become increasingly similar to well-established neural representations (i.e., more word-like).

4.2 Materials and Methods

Participants

Thirty paid volunteers (7 males; age: M=24.8, SD=4.02) took part in the experiment after giving written informed consent. All participants were right-handed and native speakers of Italian, reporting having normal or corrected-to-normal vision and no history of linguistic or neurological impairment. Participants remained unaware of the goals of the experiment until the end of the session. The present study was approved by the SISSA Ethics Committee.

Materials

Each of the four categories of stimuli (Words, Pseudowords, Nonwords, Pseudofonts) consisted of 16 five-elements long items. Words (e.g., *pasta*) were selected to be frequent singular nouns (log10 frequency: M=3.29, SD=0.12), made up of frequently occurring letter combinations (mean log10 bigram frequency: M=6.08, SD=0.47). Pseudowords (e.g., *stapa*) were constructed by rearranging the letters of the word stimuli to form novel pronounceable letter strings, also with frequent letter combinations (mean log10 bigram frequency: M=6.31, SD=0.59). Nonwords (e.g., *qnlvd*) were constructed by sampling random consonants without replacement, resulting in unpronounceable letter strings with rare or non–existent letter combinations (mean log10 bigram frequency: M=4.07; SD=1.63). Finally, pseudofont strings were constructed by combining characters from the BACS-2 serif artificial script (C. Vidal & Chetail, 2017), which were designed to closely match the visual characteristics of Latin characters (e.g., number of strokes, junctions, terminations, and serifs).

Procedure

A schematic illustration of the experimental paradigm is shown in Figure 4.1. Stimuli were presented in sequences of 360 stimuli, 72 of which were oddballs and 288 base stimuli. Base and oddball stimuli in a given sequence belonged to the same category (e.g., word oddballs embedded in a stream of word base stimuli) and differed only in terms of how often their respective tokens (N=8) appeared in the stream, with oddball tokens presented four times less frequently (i.e., 9 repetitions of each oddball token) than base tokens (i.e., 36 repetitions of each base token). The selection of base and oddball tokens involved randomly drawing two sets of 8 unique items from each stimulus category. In order to account for any systematic differences between oddball and base tokens, this procedure was performed separately for each individual participant. Once drawn, the selection of oddball and base tokens was held constant across all experimental trials for the same participant.

An experimental trial comprised a stimulation sequence, presented for 60 seconds. In each trial, stimuli were presented by sinusoidal contrast modulation at a frequency of 6 Hz, with each stimulation cycle (i.e., from a 94% light grey background to full contrast and back) reaching full contrast after 83 ms and lasting a total of 166.66 ms. An oddball stimulus was embedded every five base stimuli (i.e., oddball frequency of 1.2 Hz, thus every 833 ms). The presentation order of the stimuli was pseudo-randomized so as to eliminate consecutive item repetitions: base repetitions were separated by a minimum of 4 base stimuli, whereas oddball repetitions were separated by at least 2 oddball presentations (i.e., minimum distance 14 items). There were 5 experimental trials per condition such that the total stimulation time was 20 minutes: 60 s (trial duration) x 4 conditions (Words, Pseudowords, Nonwords, Pseudofonts) x 5 trials. Experimental trials were presented in random order

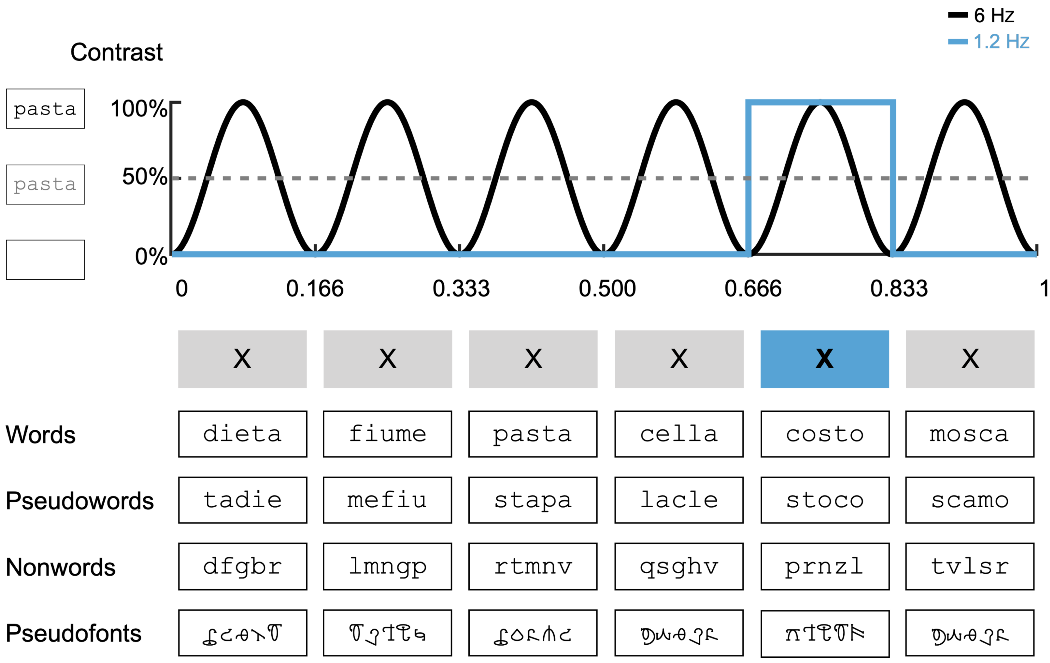


Figure 4.1: Experimental paradigm. In each sequence, stimuli were presented by sinusoidal contrast modulation at 6 Hz during 60 s. Each stimulus reached full contrast 83 ms after its onset and faded out completely after 166 ms (the duration of one cycle). Oddball stimuli appeared every fifth item at a frequency rate of 1.2 Hz (6/5 Hz). Differently from the classical FPVS-oddball design in which oddballs are embedded in a sequence of base stimuli that belong to a different category, in the present study oddballs and base stimuli were randomly drawn from the same category (X embedded in X; oddball is highlighted for illustration) and differed only in terms of their token frequency. A stimulation sequence comprised 360 stimuli with each base token repeated 36 times and each oddball token 9 times. Presentation order was pseudo-randomized to avoid immediate repetition. Examples are given for the four different conditions used in the experiment.

and were separated by a 30-second break. Each break ended with a 15-second countdown that indicated the beginning of the next trial.

Participants were run individually in a sound-attenuated and dimly illuminated room, seated at approximately 80 cm from a 27” BenQ XL2720Z monitor. Screen resolution was 1920 X 1080 pixels and refresh rate was set at 60 Hz. Stimulus display was administered by PsychToolbox-3 (Brainard, 1997, http://psychtool box.org)) on MATLAB R2015b (The MathWorks) in a Windows environment. All stimuli were presented at the center of the screen. All alphabetic stimuli (i.e., Words, Pseudowords and Nonwords) were presented in lowercase characters, using the fixed-width Courier New font, whereas Pseudofonts were presented in BACS-2 serif font. Both fonts were emboldened by 70% from their original character weight to improve visibility. Each stimulus subtended horizontal and vertical visual angles of 2.87 and 0.72 degrees, respectively. Participants were instructed to fixate a small cross (12 pixels) presented continuously at the center of the screen, and to press a button as soon as they detected a change in its color (from blue to red and vice versa), which occurred randomly 6 times within each trial, independently of the oddball-base manipulation. The sole purpose of the color-change detection task was to ensure that the participant maintained a constant level of attention throughout the stimulation. Overall, participants' performance in the color-change detection task was highly accurate (accuracy: M=97.2%, SD=0.08; reaction times: M=448 ms, SD=73) and comparable across the different experimental conditions (Words=98.2%, SD=0.05, reaction time: M=447 ms, SD=73; Pseudowords=95.5%, SD=0.11, reaction time: M=446 ms, SD=71; Nonwords=98.3%, SD=0.06, reaction time: M=447 ms, SD=67; Pseudofonts=96.8%, SD=0.09, reaction time: M=453 ms, SD=80).

EEG acquisition and Preprocessing

Electroencephalographic (EEG) activity was acquired at a sampling rate of 256 Hz using an Active Two Biosemi system (Biosemi, Amsterdam, Netherlands) with 128 active electrodes mounted on an elastic cap and positioned according to the radial-ABC system locations. Two additional electrodes served as reference (Common Mode Sense active electrode, CMS) and ground (Driven Right Leg passive electrode, DRL). The magnitude of the offset of all electrodes, referenced to the common mode sense, was held below 20 mV.

EEG data preprocessing was performed in MATLAB (MathWorks, Inc) using a combination of custom script and the EEGLAB toolbox (Delorme & Makeig, 2004). Data from each subject were band-pass filtered (0.1–100 Hz), and artifact-ridden channels were removed by visual inspection of their time series and spectra. Eye blink, muscular and electrode-pop artifacts were removed using Independent Component Analysis. After cleaning, removed channels were replaced by using spherical interpolation, and data were segmented into 60-second epochs and re-referenced to the average of all electrodes. This procedure resulted in one dataset (5 trials of 60 seconds) per participant per condition. Data from one participant were excluded from the analyses due to excessive movement artifacts in the electrophysiological data.

Frequency Analysis

Experimental trials were first averaged in the time domain, separately for each condition and each individual participant. This procedure served to reduce EEG activity that was not phase-locked to the stimulation. Data were then submitted to a Fast Fourier Transform and normalized amplitude spectra were extracted for each channel (absolute value of the FFT, divided by the number of data points). Given that the length of the epochs was 60 seconds, the frequency resolution was very high (1/60=0.0167 Hz). To account for noise variations across the frequency spectrum, a local baseline-correction was applied, which involved subtracting from each frequency bin the mean of the surrounding 20 bins (10 from each side, excluding immediately adjacent bins and bins with minimum and maximum values; as in e.g., Dzhelyova and Rossion, 2014). Base and oddball responses were defined as the sum of the baseline-corrected amplitudes at the base (6 Hz) and oddball (1.2 Hz) stimulation frequencies and their corresponding first three harmonics (base: 12, 18, 24 Hz; oddball: 2.4, 3.6, 4.8 Hz).

ROI Analysis

The EEG response at the base stimulation frequency was analyzed in an occipito-parietal area comprising twenty electrodes surrounding and including Oz (A23 in Biosemi's ABC labeling), the site typically showing maximal SSVEP responses (Norcia et al., 2015). The EEG response at the oddball stimulation frequency were examined in two predefined regions-of-interest (ROI). Following previous work that used the same type of visual stimuli (i.e., pseudofonts and letter strings, e.g., Lochy et al., 2015), the primary regions of interest for oddball responses comprised an area of five occipito-temporal sites including and around the electrode PO7 on the left, and PO8 on the right hemisphere (A10 and B7 respectively in Biosemi's ABC labeling).

Data analysis was conducted at two levels. First, in order to test the significance of the oddball response in each condition, the response of interest was averaged across the channels of each ROI for each participant, and then subjected to a one sample t-test. Second, differences between conditions were assessed through ANOVAs with Condition (Words, Pseudowords, Nonwords, Pseudofonts) as a within-groups factor. In the case of the response at the oddball frequency, the within-groups factor of Hemisphere (left, right) was also included. The absence of statistically significant effects was further corroborated via a JZS Bayes Factor (Rouder et al., 2009), which measures the relative evidence for the null vs. the alternative hypothesis, thus allowing to provide support for the null itself (Leppink et al., 2017). These analyses were performed using a Cauchy prior with the default scale value of r=0.5. We report the relative evidence in favor of the null (BF01), where a value of 1 implies equal relative evidence and values above 3 indicate evidence in favor of the null.

Cluster Permutation Test

To assess the presence of an effect in electrodes besides the ones included in the ROIs, the presence of an oddball response was additionally tested using a non-parametric clustering method (Bullmore et al., 1999) as implemented in the FieldTrip toolbox for EEG/MEG analyses (Oostenveld et al., 2011). This method provides an intuitive and straightforward solution to the multiple comparisons problem. It relies on the fact that a true effect should not be isolated, but should instead spread over adjacent electrodes, and is implemented through the following steps: (i) a statistic of interest (a t-value and the corresponding p-value, in this case) is calculated for each channel; (ii) spatially neighboring channels that yield a significant result ($p<0.05$) are grouped together into candidate clusters, and a cluster-level t-value is computed by summing their individual t-values; (iii) next, a random subset of channels have their values set to zero, and the procedure is repeated on this surrogate data. This is repeated a large number of times (5000, in this case) and each time the largest cluster-level t-value is retained, constructing in this way an empirical distribution of possible t-values under the null; (iv) finally, the p-values of the observed candidate clusters is calculated as the percentage of t-values from the null distribution that are more extreme than their cluster-level t-value (for a more detailed explanation, see Maris & Oostenveld, 2007).

In order to test for possible differences in the topographies of the effects across conditions, we first applied the cluster permutation method described above. Since no significant clusters emerged in any of the comparisons, we turned to the JZS Bayes Factor (using a default Cauchy prior with scale value of r=0.707) to assess the evidence in favor of no difference between conditions. We calculated the Bayes Factor independently for each electrode and reported the number of electrodes showing evidence in favor of the null and in favor of the alternative hypothesis.

4.3 Results

Base Stimulation Frequency

A response at the base stimulation frequency reflects the successful synchronization of the visual system to the periodic stimulation and serves to demonstrate a constant deployment of attentional resources. In all experimental conditions the base stimulation frequency (6 Hz) and its higher harmonics (12, 18 & 24 Hz) resulted in a clear response in the predefined region of interest around Oz (Words: $t_{(28)}$=9.556, p<0.001, g=1.774 [95% CI: 1.179 - 2.356]; Pseudowords: $t_{(28)}$=9.707, p<0.001, g=1.802 [95% CI: 1.202 - 2.390]; Nonwords: $t_{(28)}$=13.173, p<0.001, g=2.446 [95% CI: 1.706 - 3.174]; Pseudofonts: $t_{(28)}$=14.522, p<0.001, g=2.696 [95% CI: 2.696 - 3.482]). The scalp topography of the response was analogous to the one previously observed in studies that presented visual stimuli at the same or similar frequency rates (e.g., Liu-

Shuang et al., 2014). A one-way ANOVA revealed an effect of Condition that was marginally significant ($F(2.12, 59.32)=3.13$, $p=0.048$, Greenhouse-Geisser corrected). A subsequent JZS Bayes Factor analysis, however, revealed moderate evidence against the presence of this effect ($\mathrm{BF}_{01}=6.289$), and as such it was not submitted to further analyses.

Oddball Stimulation Frequency

ROI Analysis

Results revealed a significant oddball response in both the predefined left and right occipito-temporal regions of interest (see Figure 4.2)†.

Tokens with a low frequency of occurrence successfully elicited an entrainment at the oddball stimulation frequency when the stream of stimulation consisted of Words embedded in Words (Left ROI: $t_{(28)}=4.16$, $p=0.0003$, $g=0.77$ [95% CI: 0.35 - 1.18]; Right ROI: $t_{(28)}=3.87$, $p=0.0006$, $g=0.72$ [95% CI: 0.30 - 1.12]), Pseudowords in Pseudowords (Left ROI: $t_{(28)}=3.46$, $p=0.0017$, $g=0.64$ [95% CI: 0.28 - 1.04]; Right ROI: $t_{(28)}=3.20$, $p=0.0033$, $g=0.59$ [95% CI: 0.19 - 0.99]), Nonwords in Nonwords (Left ROI: $t_{(28)}=2.55$, $p=0.0164$,

---

[†] As a sanity check, we examined whether, in addition to the oddball stimulation frequency at 1.2 Hz (every 5$^{\text{th}}$item, 6/5 Hz), our data showed evidence for neural entrainment also at 1 Hz (every 6$^{\text{th}}$ item, 6/6 Hz), 1.5 Hz (every 4$^{\text{th}}$ item, 6/4 Hz), 2 Hz (every 3$^{\text{rd}}$ item, 6/3 Hz), and 3Hz (every 2$^{\text{nd}}$ item, 6/2 Hz). Results showed only scattered evidence for entertainment at these frequencies. Of the 32 tests that we ran (4 frequencies x 2 ROI x 4 types of stimuli), only 7 were significant: at 1 Hz, Words, right ROI: $t_{(28)}=1.89$, $p=0.035$; at 1.5 Hz, Pseudofonts, right ROI: $t_{(28)}=2.12$, $p=0.021$; and at 3 Hz (Words, right ROI: $t_{(28)}=5.68$, $p < .001$, left ROI: $t_{(28)}=3.25$, $p=0.001$; Pseudowords, right ROI: $t_{(28)}=1.83$, $p=0.039$; Nonwords, right ROI: $t_{(28)}=2.33$, $p=0.014$, left ROI: $t_{(28)}=1.70$, $p=0.05$). This is in stark contrast with the very systematic emergence of a response at the frequency of oddball presentation.

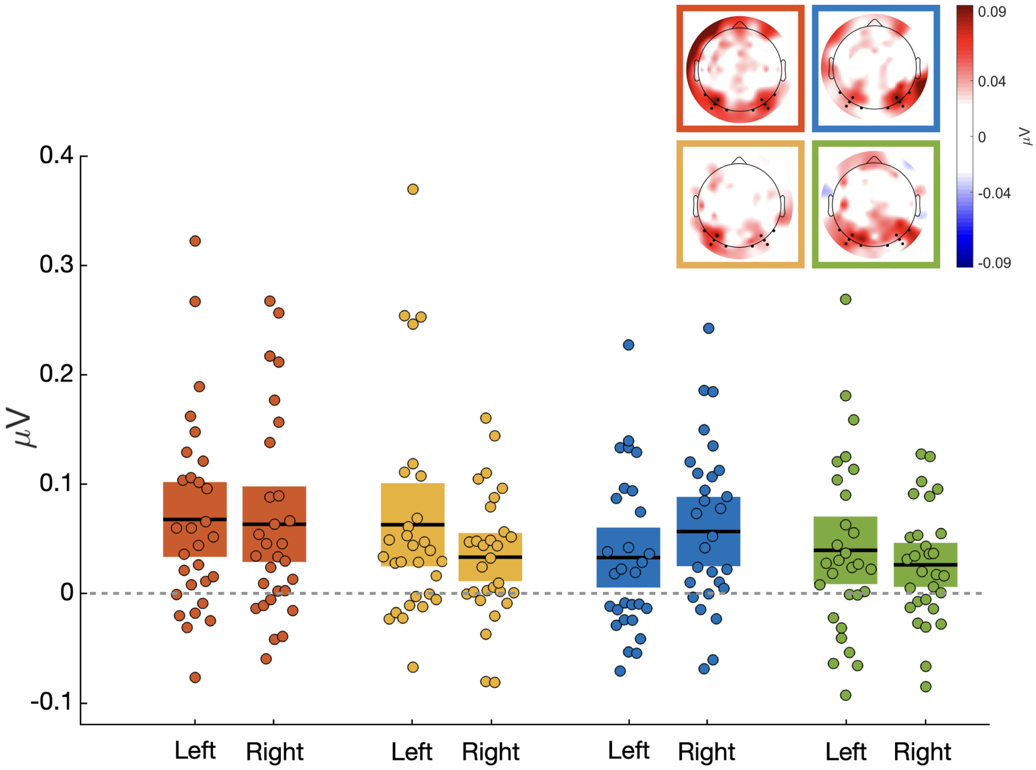


Figure 4.2: Grand-averaged token frequency response estimated as the summed baseline corrected amplitudes for the oddball frequency (1.2 Hz) and its harmonics (2.4, 3.6, 4.8 Hz) for the different conditions (Words in red, Pseudowords in yellow, Nonwords in blue, Pseudofonts in green) in the left and right occipito-temporal regions of interest, marked in the corresponding scalp topographies. Boxes depict the 95% t-interval around the mean and dots represent single participants. The dashed line illustrates the level of noise.

g=0.47 [95% CI: 0.08 - 0.85]; Right ROI: $t_{(28)}$=3.79, p=0.0007, g=0.70 [95% CI: 0.29 - 1.10]), and Pseudofonts in Pseudofonts (Left ROI: $t_{(28)}$=2.66, p=0.0127, g=0.49 [95% CI: 0.10 - 0.88]; Right ROI: $t_{(28)}$=2.79, p=0.0093, g=0.59 [95% CI: 0.13 - 0.90]). A two-way ANOVA failed to indicate any significant effect of either Hemisphere ($F(1, 28)$=0.440, p=0.5112, η^2=0.001) or Condition ($F(1, 28)$=0.440, p=0.2993, η^2=0.001); additionally, the interaction between the two terms was not significant ($F(3, 84)$=2.343, p=0.7885, η^2=0.015). A JZS Bayes Factor analysis corroborated the absence of statistically significant effects for Hemisphere (BF_{01}=6.134), Condition (BF_{01}=5.617) and their interaction (BF_{01}=250).

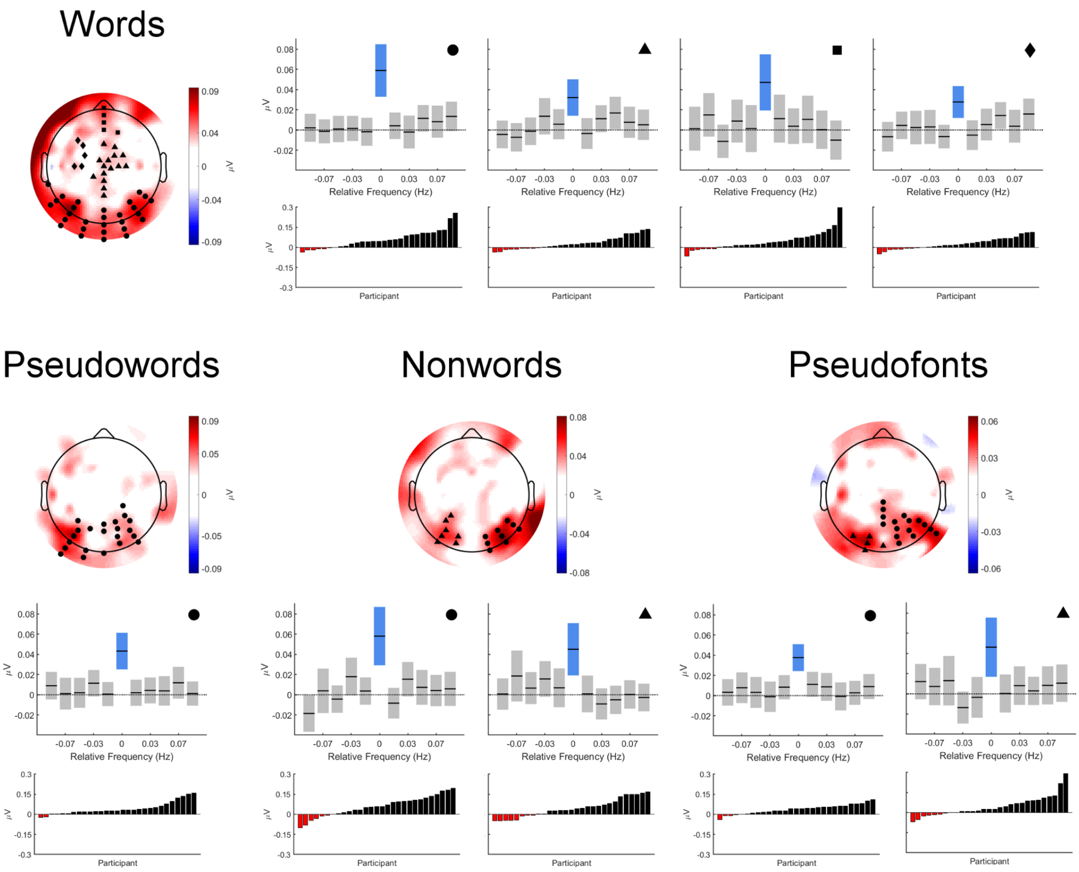
Cluster Permutation Analysis

As illustrated in Figure 4.3, all four conditions revealed a strong and reliable response at the oddball stimulation frequency (1.2 Hz) and its higher harmonics (2.4, 3.6 & 4.8 Hz) reflecting sensitivity to the token frequency manipulation. In the Words condition, this emerged in four electrode clusters located (i) in a posterior area that comprised occipito-temporo-parietal sites ($t_{(28)}$=174.27, p=0.0002, d=0.58 [95% CI: 0.18 - 0.97]); (ii) in central medial sites ($t_{(28)}$=77.60, p=0.007, d=0.48 [95% CI: 0.09 - 0.86]); (iii) over mid-frontal electrodes ($t_{(28)}$=29.43, p=0.408, d=0.55 [95% CI: 0.15 - 0.93]); and finally, (iv) in a small lateralized left-central region ($t_{(28)}$=26.14, p=0.0488, d=0.49 [95% CI: 0.10 - 0.87]). In the Pseudowords condition, the discrimination response emerged in one posterior cluster localized across occipito-temporo-parietal sites ($t_{(28)}$=119.40, p=0.0006, d=0.50 [95% CI: 0.11 - 0.89]). In the Nonwords condition, a significant response was elicited in two occipito-temporo-parietal clusters, one on the right ($t_{(28)}$=58.42, p=0.0128, d=0.60 [95% CI: 0.20 - 1.00]), and one on the left hemisphere ($t_{(28)}$=37.95, p=0.0314,

d=0.50 [95% CI: 0.11 - 0.89]). Finally, Pseudofonts yielded a similar scalp topography as the Nonwords condition, again with one significant occipito-temporo-parietal cluster on the right ($t_{(28)}$=87.30, p=0.0008, d=0.51 [95% CI: 0.11 - 0.89]) and one on the left hemisphere ($t_{(28)}$=26.07, p=0.0434, d=0.48 [95% CI: 0.09 - 0.87]). There were no candidate clusters to indicate significant differences in the distribution of the oddball response between conditions. This lack of statistical evidence was further corroborated by JZS Bayes Factor analyses, which provided evidence against cross-condition differences in the scalp topography of the oddball response (Electrodes showing evidence in favor of the null ($BF_{01}>3$): Words vs. Pseudowords=66, Words vs. Nonwords=73, Words vs. Pseudofonts=61; Pseudowords vs. Nonwords=68, Pseudowords vs. Pseudofonts=74; Nonwords vs. Pseudofonts=84. Electrodes showing evidence in favor of the alternative ($BF_{10}>3$): Words vs. Pseudowords=0, Words vs. Nonwords=0, Words vs. Pseudofonts=0; Pseudowords vs. Nonwords=1, Pseudowords vs. Pseudofonts=1; Nonwords vs. Pseudofonts=1).

4.4 Discussion

The present study examined whether neural discrimination can be generated implicitly by the statistical structure of a rapidly changing visual stream. In an FPVS-oddball design, participants were exposed to rapid streams of visual stimuli (6 Hz), embedded with oddballs that appeared periodically every fifth item (1.2 Hz). Crucially, oddballs and base stimuli belonged to the same category and differed only in terms of the frequency with which their individual tokens occurred in the stream (i.e., oddball tokens appeared less often than base tokens). Results revealed a significant neural signal at the oddball stimulation rate and its harmonics, reflecting a selective response to oddballs


Words

Pseudowords

Nonwords

Pseudofonts

Figure 4.3: Grand-averaged token frequency response for the different conditions resulting from the cluster permutation test. In the scalp topographies different symbols depict the significant clusters. The plots represent the corresponding data with the oddball response centered at 0. Boxes depict the 95% t-interval around the mean and the dotted line illustrates the level of noise. For illustration purposes, the analogous response in the 10 neighboring frequency bins is displayed. The distribution of individual oddball responses for each participant in each cluster is also reported.

relative to base stimuli. Such a response is of similar nature to the one observed in perceptual categorization studies, indexing the brain's ability to distinguish between two different categories of stimuli (e.g., words vs. nonwords, Lochy et al., 2015; faces vs. objects, Retter and Rossion, 2016). Importantly, however, in the absence of any preexisting distinction, or other systematic differences (e.g., order of token presentation), between oddballs and base stimuli, the presence of an oddball response in the current study signifies the discrimination between two groups of items formed purely on the basis of their token frequency in the input stream: high versus low frequency tokens. Additionally, results showed that such a discrimination response was elicited across a wide span of stimuli, ranging from strings of unfamiliar, non-alphabetic characters to fully fledged, frequent words, indicating a frequency-based grouping that occurred independently of stimulus familiarity.

The observed frequency-of-occurrence effect emerged automatically, while participants engaged in an orthogonal task that did not require explicit processing of the experimental stimuli. Indeed, the ability of the human brain to implicitly learn from the statistical properties of an input stream is widely attested across a variety of research domains (e.g., Christiansen, 2019; R. Frost et al., 2019; see also Santolin and Saffran, 2018, for a review across species). Implicit statistical learning is attributed to a fundamental learning mechanism that enables us to discover patterns of regularity embedded in our sensory environment and appears to be involved in several key cognitive functions including category learning. A well-known illustration of this was provided by Maye et al. (2002), who showed that the frequency distribution of category exemplars to which infants are exposed influences the formation of phonemic category boundaries. Specifically, when infants were exposed to a bimodal frequency distribution, whereby prototypical phonemes occurred frequently, and intermediate category phonemes (i.e., falling between phonemic categories) were infrequent, they were more likely to distinguish between prototypes of two phonemic categories. Conversely, when they were exposed to a unimodal frequency distribution, whereby intermediate category phonemes occurred most frequently, infants were less likely to make such distinction (see also Maye et al., 2008; Rosenthal et al., 2001). Consistent with these findings, the present study provides evidence for participants' sensitivity to the distributional properties of the input. Remarkably, however, we show that even a simple frequency-of-occurrence difference appears to be sufficient to group separately stimuli that are otherwise indistinguishable. Furthermore, we demonstrate that this process operates dynamically on novel and familiar stimuli alike (i.e., overriding any previous representational knowledge). Direct support for this phenomenon is provided by a recent study conducted in the context of artificial grammar learning. In a series of experiments, Marino et al. (2020) showed that infants relied on the frequency which words occurred in the artificial grammar to implicitly categorize stimuli as function and content words; as in real languages function words appeared more frequently than content words. We suggest that these observations denote the deployment of a fundamental mechanism that is intimately tuned to frequency patterns and underpins abstract category bootstrapping. Using frequency as a potential cue to bootstrap categories can be easily conceptualized in the domain of language learning, whereby frequency-related effects are critical for the emergence of linguistic categories (for a theoretical discussion, see Ellis, 2002). Learning idioms, syntactic patterns, but also plausible word forms (i.e., comprising legal ortho-phonotactic patterns, prototypical bigrams or meaningful units) is an ability that hinges on how frequently a listener, or a reader, experiences instances of the existing categories in a linguistic system. Importantly, the discovery of such linguistic categories unfolds automatically and effortlessly, despite the lack of explicit instructions and of an overt intention to learn.

An additional, significant aspect of the current findings is that they serve to demonstrate the potential of the FPVS-oddball paradigm as a novel approach to the study of statistical learning. Recent critical analyses of the existing literature highlight the need to methodologically diversify this important field of research, which has surprisingly been confined to, and limited by, a small range of experimental paradigms (for critical reviews, see R. Frost et al., 2019; Siegelman et al., 2018). Compared to these, the FPVS methodology enjoys several advantages. Specifically, in a typical statistical learning experiment, learning is tested offline during a separate test-phase, which follows participants' passive exposure to an input stream (i.e., the familiarization phase). Furthermore, newly acquired knowledge is usually measured through participants' performance on a behavioral task that requires them to deliberate over learned material in order to make explicit decisions about stimuli that either follow or violate the regularities present in the input stream (i.e., close variations of the tasks used in the seminal work in the field; e.g., Saffran et al., 1996). However, these measures, in addition to learning, are likely to reflect cognitive operations that relate to participants' reflective and decision-making abilities (see, e.g., Christiansen, 2019). By contrast, with FVPS, learning can be derived directly from exposure to the stream of information.

A direct measure of learning can also be obtained by behavioral methodologies that aim to track statistical learning online. This is usually achieved by measuring response time differences between predictable and unpredictable stimuli in target recognition or self-paced tasks throughout familiarization (Franco et al., 2015; Siegelman et al., 2018). Relative to these approaches, FPVS does not require participants to actively engage or attend to the experimental stimuli. As a consequence, any neural signal elicited by the statistical structure of the input does so automatically and remains uncontaminated by other task-specific cognitive demands. This specific feature of FPVS offers an easy and straightforward way to investigate the automaticity of statistical learning in the absence of selective attention to the input (see Turk-Browne et al., 2005, for a related discussion).

It should be noted, however, that recording the changes elicited by the ongoing exposure to regularities is pivotal for measuring learning online; capturing the learning trajectory offers important insights into the dynamic process of assimilating the statistical regularities present in the environment (Siegelman et al., 2018). In the context of FPVS, this learning process could be reflected by incremental changes to the oddball response as a function of stimulation time: in the present study one would expect the sensitivity to the frequency-of-occurrence effect to grow stronger with participants' exposure to the statistical structure of the input stream. The present study was not designed to investigate the evolution of the frequency-based effect over time; in fact, the results of a post-hoc exploration of this issue could not allow any firm conclusion (the details and results of these analyses are reported in the Appendix to this Chapter). However, this exploration does show the importance of a few methodological details if we are to capture the temporal evolution of the signal. For example, given that the frequency resolution of the EEG spectrum is inversely proportional to the duration of the signal, the use of sufficiently long stimulation trials is necessary to counteract the loss of frequency resolution that results from segmenting the stimulation period into smaller epochs (i.e., time windows). Additionally, in order to reduce variability in the measurement of the oddball response, care should be taken so that the critical manipulation (i.e., the difference in frequency-of-occurrence between base and oddball tokens in the present study) within a given time window is comparable across participants. In order to establish the potential contribution of FPVS designs to this field, future work should build upon these considerations and assess whether this novel methodology can successfully capture the neural traces of the temporal evolution of learning upon exposure.

Electrophysiological methodologies that rely on event-related potentials can also provide neural evidence for statistical learning. Compared to FPVS, ERP approaches offer an ideal way to examine the time course of a neural response relative to the onset of a stimulus and have been shown to effectively capture online statistical learning (Abla et al., 2008; Sanders et al., 2002). Due to the high-frequency rate of stimulation, in FPVS there is an overlap between the responses elicited by the different stimuli making it difficult to delineate the time course of a response with respect to the stimulus onset. On the other hand, FPVS benefits from two distinctive advantages. The first one lies in the objectivity with which a response is measured. FPVS provides a response that is observed at a predefined frequency band, thus eliminating the subjectivity that can accompany the identification of ERP components. Second, FVPS is a highly sensitive approach and particularly suited for subtle manipulations. This is due to the fact that the FPVS response is confined to a small number of discrete, narrow frequency bands and as such, it is minimally contaminated by irrelevant noise sources (i.e., which tend to distribute throughout the EEG frequency spectrum; for further discussion on the strengths and weaknesses of FPVS, Rossion, 2014).

Notably, this new methodological approach opens up a new way to address questions that can lead to a further specification of the mechanisms that underpin statistical learning. In particular, the present findings provide novel evidence that statistical learning emerges under high temporal constraints, and can thus operate on a timescale that has so far remained virtually unexplored: the presentation of a given stimulus lasted less than 166 ms and its processing was masked by both a preceding and a following stimulus. Can this type of learning unfold on an even faster timescale? Furthermore, the frequency difference that elicited neural grouping in the present study was 9 repetitions of each oddball token as opposed to 36 repetitions of each base token (i.e., 1/4 ratio). What might be the minimum relative difference required to give rise to the kind of discrimination response that was observed? Finally, beyond frequency of occurrence whether more elaborate statistics like the transitional probability of events can be learned implicitly under these stimulation conditions remains to be established.

In the same light, the present findings contribute to the statistical learning literature by stressing the importance of non-associative statistical cues – the distribution of token frequency, in this specific case – to implicit learning. Following on the path set by the earliest, seminal work in the field (e.g., Reber, 1967; Saffran et al., 1996), most statistical learning studies have focused their investigations on conditional statistics. Indeed, the substantial uniformity that characterizes this research field has been especially highlighted in a recent critical review by R. Frost et al. (2019), who discuss its impact on the scope of the empirical findings and ultimately, on advancing our understanding of the underlying statistical learning mechanisms. While the salience of conditional statistics is indisputable (Avarguès-Weber et al., 2020), these are not the only type of statistics that learners attend (Thiessen et al., 2013). In this context, we consider the present set of data as a way to highlight the diversity of the probabilistic information that characterizes our perceptual world, and how powerful distributional cues – somewhat neglected in previous research on statistical learning – can be in driving our learning.

An additional aspect of our findings worth mentioning is the implications they carry for FVPS research. The susceptibility of the approach to the statistical structure of the stimulus sequence challenges previous evidence for category-selective neural discrimination to determine if, and to what extent, the evoked responses have been confounded by the relative token frequency of base and oddball stimuli or the presence of other embedded regularities. Concurrently, our findings call future FPVS work to account for implicit statistical learning phenomena in the design of the stimulation stream in order to avoid such contamination in the discrimination responses.

Finally, considering the potential neural mechanisms that underlie the emergence of the discrimination response in the present study, we suggest that this can be accounted for by a bottom-up process of context-dependent neural adaptation. The observed frequency-of-occurrence effect could index a difference in across-item repetition suppression (i.e., delayed repetition, Henson et al., 2004), with the frequently repeated base tokens undergoing greater reduction in stimulus-evoked neuronal activity compared to oddball tokens, which were repeated less frequently (see also Radtke et al., 2021). Alternatively, the differential response to oddball stimuli could reflect an effect of expectation (or surprise), similar in kind to that observed in the MMN response (e.g., Kimura et al., 2011; Stefanics et al., 2015) as interpreted within the framework of predictive coding models (e.g., Friston, 2005; Garrido et al., 2009). According to this, our brain generates expectations about incoming sensory events on the basis of our previous experiences. Encountering an unexpected, rare stimulus would thus result in a larger prediction error relative to a frequent and expected one. Within this framework, a frequency-based oddball response can be conceptualized as a difference in prediction error between stimuli with a high probability of occurrence (base tokens) versus stimuli with a low probability of occurrence (oddball tokens). Importantly, the generation of stimulus expectations in the current oddball design would arise from the distributional properties of the input via the integration of information across several stimuli (for further evidence of the effect of distributional statistics on MMN, see e.g., Koelsch et al., 2016).

Interestingly, using a more conventional oddball design Amado and Kovács (2016) demonstrated that the relative contribution of repetition suppression and expectation effects to the visual MMN is modulated by stimulus category. Specifically, they showed that in the case of faces and chairs, the visual MMN was largely due to repetition suppression, whereas in the case of single real and false (i.e., similar to our pseudofonts) letters, the vMMN was mainly explained by surprised-related differences. Separating the relative effects of these neural mechanisms on the FPVS-oddball response was beyond the scope of our study (but see Feuerriegel et al., 2018). Nevertheless, we note that our results indicate that the observed frequency-based oddball response emerged equally for different stimulus categories, ranging from entirely novel (e.g., strings of pseudofonts) to very familiar (e.g., words) stimuli. This suggests that novel distributional information can be rapidly acquired in the context of an oddball experiment, even if it departs from the distributions learned over a lifetime, attesting to the versatility of the brain when it comes to learning statistical information.

In conclusion, the present study capitalized on FPVS and EEG to provide evidence for neural discrimination based purely on the distribution of token frequency within a rapidly changing stream of visual stimuli. This discrimination response emerged implicitly and independently of stimulus familiarity, thus reflecting the operation of a fundamental mechanism that is prone to capture the statistical structure embedded in the environment. These findings showcase the potential of FVPS for providing a neural measure of implicit statistical learning and open up a new promising avenue for this line of research.

Chapter 5

Study IV: Co-occurrence Statistics in Letter Identification[*]

When presented with text, skilled readers recognize words within the span of a glimpse. Visual information is rapidly encoded, so that single letters – these artificial visual objects that accompany readers of alphabetical languages in their everyday life – come together into a unique code, which is then used to access one of the hundreds of thousands of possible lexical representations. The validity of such code relies on the ability to extract letter information from the visual display at hand, as well as on the linguistic knowledge available to the reader. Orthographic processing is the interface that allows such integration of visual and linguistic information (Grainger, 2018), and can thus be regarded as the first stage of visual word identification.

Single word reading relies on abstract letter identities (beyond the specifics of case, size and font), together with their position within a string. Nevertheless, reading is also a visual skill (Carr, 1986; Nazir & Huckauf, 2007), and thus draws heavily on visual information. Consistent evidence supports the role of visual and oculomotor skills in reading acquisition (Aghababian & Nazir, 2000;

---

[*] From De Rosa, M., & Crepaldi, D. (2021). *Co-occurrence statistics affect letter processing.* Manuscript in preparation.

Ducrot et al., 2013; Grainger, Dufau, et al., 2012; Jeon et al., 2010; Kwon et al., 2007; Lobier et al., 2013; Sperlich et al., 2016), and indicates that atypical visual processing might be involved in reading impairments (Bellocchi, 2013; Franzen et al., 2021; Gori & Facoetti, 2015; Perea et al., 2012; Stein & Fowler, 1981; Vernet et al., 2021).

Even for skilled readers, obtaining orthographic information is subordinated to overcoming perceptual limitations. A first bottleneck is visual acuity, which steeply drops outside of the center of fixation (Adler & Fliegelman, 1934; Sloan, 1951) with a reduction of about 60% at 1° of eccentricity (Wertheim, 1894). Another major challenge is posed by crowding, the deteriorated perception of a target caused by the presence of nearby flankers (Bouma, 1970; Flom et al., 1963; Townsend et al., 1971; see Levi, 2008; D. Whitney and Levi, 2011, for recent reviews). While the nature of its underpinning mechanisms is still a hotly debated topic (Balas et al., 2009; Francis et al., 2017; Greenwood et al., 2009; Harrison & Bex, 2017; Herzog et al., 2015; Manassi & Whitney, 2018; Pelli et al., 2004; Rosenholtz et al., 2019; Van den Berg et al., 2010), crowding depends on the distance between the target and the flankers. Therefore, it affects the processing of letters in close spatial proximity, such as the components of a single word, both in peripheral (e.g., Bricolo et al., 2015; Pelli et al., 2007) and foveal reading (Grainger, Dufau, & Ziegler, 2016). While excessive inter-letter spacing is found to disrupt whole-word perception (Cohen et al., 2008), a slight increase alleviates crowding, thus resulting in faster lexical decision latencies (Perea et al., 2011); coherently, the reduction of inter-character distance compared to normal spacing is detrimental for word identification (Montani et al., 2015).

The combined effects of visual acuity and crowding play a major role in letter processing, as attested by the profile of the serial position functions obtained in letter identification tasks (Grainger, Dufau, & Ziegler, 2016). Performance in recognizing letters in a five-item long string is generally ideal for the foveated letter, where acuity is maximal. Letters out of this area are instead negatively affected by their reciprocal close proximity, with the notable exception of the outer items, for which performance is advantaged. As a result, letter identification performance as a function of absolute position typically results in a W-shaped and a M-shaped patterns for accuracy and latency, respectively (Averbach & Coriell, 1961; Haber & Standing, 1969; Ktori & Pitchford, 2008; Mason, 1975; Merikle et al., 1971; Pitchford et al., 2008; Schwantes, 1978; Stevens & Grainger, 2003). Crowding mechanisms have been associated with the facilitated performance on exterior letters, as they are flanked by only one item, compared to the non-fixated inner positions, which are negatively affected by the presence of two surrounding letters.

However, in spite of a purely visual account of this pattern of results, W/M-shaped serial position functions are more often specifically associated with readable alphanumeric stimuli, as opposed to unreadable symbols (Mason, 1982; Mason and Katz, 1976; Tydgat and Grainger, 2009; but see, e.g., Castet et al., 2017 for a different view). Additionally, the first letter of the string enjoys a marked and unparalleled advantage (Aschenbrenner et al., 2017; Scaltritti & Balota, 2013; Scaltritti et al., 2018), a finding that cannot be accommodated by crowding mechanisms alone. Several accounts ascribe these patterns to peculiarities of the literate brain (e.g., Aschenbrenner et al., 2017; Tydgat & Grainger, 2009; Winskel et al., 2018), consistently with the numerous testaments to top-down influences of higher-order linguistic knowledge on perceptual processes. Among them, the so-called *word superiority effect* is perhaps the most well known – the finding that individual letters are more easily identified when embedded in real words rather than anagrams, random strings or even in isolation (Carr et al., 1979; Cattell, 1886; Reicher, 1969; Wheeler, 1970). In keeping with this phenomenon, recent neuroimaging studies showed representational boosting in early visual areas for individual letters in lexical contexts (Heilbron et al., 2020), a finding that is also consistent with evidence of attenuated crowding for letters in words, compared to pseudowords (Montani et al., 2015).

From word frequency to word meaning, to pronounceability and orthographic legality, both lexical and sublexical sources of information have been considered as drivers of top-down influences (Baron & Thurston, 1973; Krueger, 1975). One hypothesis is that a lifetime exposure to text might result not only in lexical and sublexical discrete representations, but also in an implicit knowledge of the distributional properties inherent in the language, which in turn could affect reading. Words are, after all, combinations of letters, assembled according to ortho-phonotactic rules. The textual environment is thus potentially rich in statistical cues that could effectively support skilled readers in letter and string processing. This conjecture is consistent with the remarkable sensitivity to regularities exhibited by the human cognitive system, a phenomenon broadly known as *statistical learning* (recently reviewed in, e.g., Armstrong et al., 2017; Aslin, 2017; Christiansen, 2019; R. Frost et al., 2019; E. L. Newport, 2016). Statistical learning is a domain general mechanism that encompasses visual (Fiser & Aslin, 2002), tactile (Conway & Christiansen, 2005) and auditory domains (Saffran et al., 1999), and permeates a variety of cognitive phenomena, such as memory (Kóbor et al., 2017), object representation (Lengyel et al., 2019), predictive processing (Morgan et al., 2019) and language acquisition (Saffran & Kirkham, 2018).

This pervasive aptitude has been often associated with reading acquisition and execution, and could constitute a plausible interface between visual and linguistic processes. Examples come from learning studies with pseudo-linguistic material, such as Chetail (2017), in which participants implicitly extrapolated frequent bigrams from a train of stimuli, and Lelonkiewicz et al. (2020), where affix-like units were chunked on the sole basis of their distributional statistics. Furthermore, patterns of regularity affect readers' eye movements in sentence reading (Snell & Theeuwes, 2020), and statistical learning abilities have been associated with reading development and proficiency (Arciuli and Simpson, 2012; von Koss Torkildsen et al., 2019, even if with some experimental caveats, as duly reported in, e.g., Arciuli and Torkildsen, 2012; Schmalz et al., 2017).

The present study investigates the role of statistical learning at the interface between visuo-attentional and linguistic processes. Specifically, we asked whether co-occurrence regularities inherent in the natural language influence letter identification, and contribute to overcome crowding phenomena. To this aim, we briefly exposed skilled readers to five-letter strings of consonants; critically, letters in the crowded positions (i.e., second and fourth) appeared embedded in either a highly (e.g., B in M**B**L) or poorly (e.g., B in P**B**G) statistically coherent context, quantified as transitional probabilities between adjacent letters . We hypothesized that, given that edge and foveated letters are perceived more easily, a statistical relation with crowded letters could provide a relevant source of contextual information to overcome the ambiguity of an excessive, and faulty, feature integration. In Experiment I, participants engaged in a two-alternative forced choice task with whole strings (a target and a distractor, e.g., Adelman et al., 2010), which differed by one letter (e.g., M**B**LSD vs. M**C**LSD). Experiment II included both a Reicher-Wheeler task on individual letters (Reicher, 1969; Wheeler, 1970) and a Same-Different matching task (Nickerson, 1965), with the introduction of time constraints. Experiment III had participants perform a Same-Different task on the same stimuli rendered as pseudo-characters from the BACS-2 font (C. Vidal & Chetail, 2017), so that letter identities could be disrupted while preserving the low-level visual features of the original configurations.

5.2 Experiment I: Materials and Methods

Participants

Fifty-four Italian skilled readers (17 males; age: *M*=25.03, *SD*=3.90; 5 left-handed) volunteered in the experiment, after giving written informed consent. They reported having normal or corrected-to-normal vision, and no history of linguistic or neurological impairment. The study was approved by the SISSA Ethics Committee.

Materials

Ten consonants were chosen as target letters (B, C, G, L, M, N, P, R, S, T). For each of them, single letter transitional probabilities (TP) were obtained for all the consonants in the Italian alphabet, as attested in SUBTLEX-IT (Crepaldi et al., 2013) on the basis of position unconstrained type frequency. Particularly, the forward probability of a letter X to *precede* a letter (e.g., B) was defined as:

$$probability\, of\, X_{\mathrm{n-1}}|B_{\mathrm{n}} = \frac{frequency\, of\, XB}{frequency\, of\, B}$$

Conversely, the backward probability was quantified as:

$$probability\,of\,Y_{\mathrm{n+1}}|B_{\mathrm{n}} = \frac{frequency\,of\,BY}{frequency\,of\,B}$$

and expressed the probability of a letter Y to *follow* the letter B. For each target (e.g., B), we selected a letter with high forward transitional probability (e.g., $\mathrm{M}_{\mathrm{n-1}}$) and one with high backward transitional probability (e.g., $\mathrm{L}_{\mathrm{n+1}}$), so to obtain a highly coherent triplet for each target (i.e., M**B**L). Conversely, low coherence triplets (e.g., P**B**G) were constructed by selecting letters with low transitional probabilities forward (e.g., $\mathrm{P}_{\mathrm{n-1}}$) and backward (e.g., $\mathrm{G}_{\mathrm{n+1}}$) to the target (i.e., B). High and low TP triplets differed also for their written frequency (as reported in Table 5.1). For task related purposes, each triplet was then paired with a distractor, differing solely for the middle letter, to serve as an alternative in the task (e.g., M**B**L was paired with M**C**L). Crucially, distractors showed less extreme, “neutral” transitional probabilities compared to the corresponding target triplets (included in Table 5.1).

Coherence was orthogonally manipulated with position by embedding high and low coherence triplets into strings of five letters, so that the target item would appear in both the second (e.g., M**B**LSD and P**B**GVN) and the fourth position (e.g., DVM**B**L and LNP**B**G) in the two contexts.

The stimulus set comprised also items with letter-changes occurring in the remaining positions (i.e., first, third and fifth). This allowed us to ensure that participants would not strategically direct their attention to the positions where we manipulated TP, but also to replicate the serial position function generally observed for letter-search tasks with five-letter strings. As a result, we had a total of 100 unique items (10 target letters x 5 positions x 2 contexts), each of which was presented twice to each participant, in a pseudo-randomized

	TP Forward	**TP Backward**	**Trigram Frequency**
High Coherence			
Target	0.080 (0.045)	0.120 (0.121)	3.499 (1.744)
Distractor	0.025 (0.020)	0.029 (0.034)	2.498 (1.436)
Low Coherence			
Target	0.001 (0.001)	0.002 (0.002)	0.599 (0.658)
Distractor	0.007 (0.012)	0.023 (0.016)	1.986 (1.314)

Table 5.1: Stimuli Features (mean and standard deviation).

order so to avoid close repetitions.

Apparatus

Each experimental session took place in a quiet dark room. Participants were seated at 57 cm from a BenQ XL2720Z monitor (27”, 1920x1080 pixels, 144 Hz); viewing distance was kept constant throughout the experiment by means of a head-and-chin rest. Eye movements were monitored online using a Eyelink DM-890 (SR Research Ltd, Canada), at a sampling rate of 1000 Hz; this allowed a stringent control of the participants’ eye position upon the presentation of the probe stimulus (Castet et al., 2017). Stimuli were rendered as uppercase characters from the Courier New font, and displayed at the center of the screen in black on a light gray background [RGB: 160, 160, 160]. Characters held a center-to-center distance of 0.6° of visual angle, thus occupying positions $-1.2°$, $-0.6°$, 0°, +0.6°. +1.2° from the center of the screen. Participants prompted their responses through a high precision two–button CyNexo response pad (http://www.cynexo.com), based on an Arduino processor (http://www.arduino.cc). Experimental sessions were administered via PsychToolbox-3 (Brainard, 1997; http://psychtoolbox.org/)

on MATLAB R2015b (The Mathworks) in a Windows environment.

Procedure

A schematic view of the trial timeline is presented in Figure 5.1. The experiment began with a four-point-calibration procedure, which was repeated until validation error was below an average of 1° of visual angle.

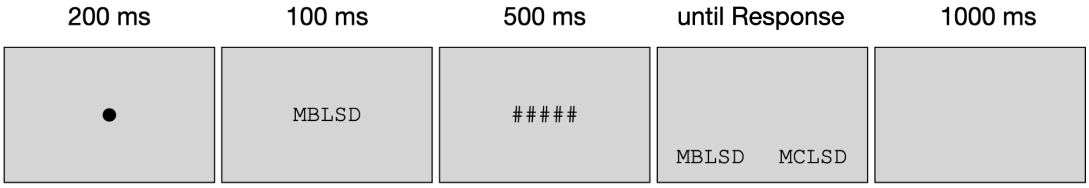


Figure 5.1: Representation of the experimental procedure adopted in Experiment I.

A black fixation dot (10 pixels in radius) was presented at the center of the screen, on a light gray background [RGB: 160, 160, 160]. Participants were instructed to continuously fixate the dot for 200 ms in order to trigger the beginning of a trial; extra calibrations were performed every time participants did not succeed in holding the fixation. Correct and continuous fixation would result in the appearance of the probe, which stayed on screen for 100 ms and was then backward masked by a string of five hash marks, presented for 500 ms. The string duration is in line with previous studies adopting consonant strings (e.g., Castet et al., 2017; Tydgat and Grainger, 2009; but see C. Whitney, 2001 for a related discussion in the case of lexical items). Two five-letter options appeared below the center of the screen (−10°), one to the left and one to the right of the probe location, and stayed on the screen until response. Consecutive trials were separated by a jittered interval of 1 second.

Each session also comprised one example, ten practice trials and three breaks. Calibration and validation were repeated at the end of each break.

Data Analysis

One subject was below 60% in overall accuracy and was thus excluded from further analyses, together with individual anticipatory responses of less than 200 ms (0.074%).

Accuracy was analyzed through generalized linear mixed-effects models with crossed random intercepts for subjects and trials (Baayen et al., 2008), as implemented in *lme4* (Bates et al., 2007) and *lmerTest* (Kuznetsova et al., 2017). Where applicable, post-hoc comparisons were performed through the *multcomp* (Hothorn et al., 2016) and *emmeans* (Lenth, 2019) packages. We ran two separate analyses. The first was performed on all trials, with Position as the main effect of interest, to assess the presence of a serial position function consistent with previous findings (e.g., Castet et al., 2017; Tydgat & Grainger, 2009). Accuracy on the preceding trial was the only other fixed effect improving the model's goodness of fit (even if just marginally, χ^2=3.208, p=0.073), and was thus included in the final model. A second analysis focused on the core manipulation and only included the trials where the target letters were in Position 2 or 4, that is, the positions featuring the experimental manipulation. In this analysis, we assessed the effects of Position (2 vs. 4), Context (high vs. low coherence) and their mutual interaction.

5.3 Experiment I: Results

The absolute position within the string was found to significantly modulate the accuracy with which participants selected the correct option (χ^2=341.704,

$p<0.001$). The resulting serial position function is shown in Figure 5.2A. Post-hoc comparisons (Table 5.2) revealed that outer positions (i.e., positions 1 and 5) elicited significantly more accurate responses compared to internal ones (i.e., position 2, 3 and 4).

Positions	**Estimate**	**Std. Error**	**z value**	**Pr(>| z |)**	
1 - 3	2.336	0.142	16.400	<0.001	***
2 - 3	0.061	0.110	0.561	0.985	
4 - 3	−0.077	0.110	−0.703	0.955	
5 - 3	0.430	0.112	3.843	<0.001	**
2 - 1	−2.274	0.142	−15.948	<0.001	***
4 - 1	−2.413	0.142	−16.961	<0.001	***
5 - 1	−1.905	0.143	−13.252	<0.001	***
4 - 2	−0.139	0.110	−1.263	0.710	
5 - 2	0.368	0.112	3.283	0.008	**
5 - 4	0.507	0.111	4.539	<0.001	***

Table 5.2: Accuracy across Positions, Post-hoc Comparisons (Experiment I).

Figure 5.2B shows the results of the analysis conducted only on the trials of interest, that is, those exhibiting the contextual manipulation (high vs. low coherence) in the crowded positions (2 and 4). We observed a significant main effect of Context ($\chi^2=6.743$, $p=0.009$), indicating that highly coherent triplets (e.g., M**B**L) elicited more accurate responses compared to less coherent ones (i.e., P**B**G; $\beta=0.43$, $SE=0.16$). The analysis revealed a marginal effect of Position ($\chi^2=3.698$, $p=0.0544$) and no significant interaction between Context and Position ($\chi^2=2.237$, $p=0.134$).

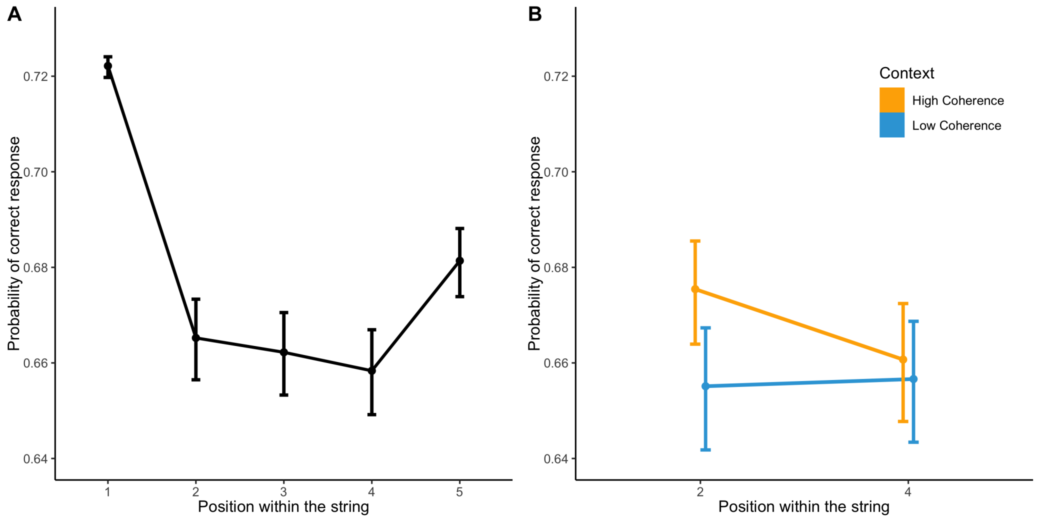


Figure 5.2: Model estimates for probabilities of correct responses (A) across all positions and (B) for position 2 and 4, as modulated by context in Experiment I. Error bars represent 95% confidence intervals.

5.4 Experiment I: Discussion

Experiment I examined accuracy as a function of letter co-occurrence statistics in a two-alternative forced choice task. Skilled readers were briefly exposed to strings of five letters, which they had to recognize between two whole-string alternatives differing just in one element (e.g., M**B**LSD vs. M**C**LSD). Critically, participants were more accurate in their choice when the differing letter was embedded in high TP contexts (e.g., M**B**L), as compared to less coherent ones (e.g., P**B**G). Therefore, our findings suggest that skilled readers capitalize on letter regularities that are consistent with their previous experience with written language.

The contextual facilitation effect emerged in a task that is expected to be affected by visual constraints, like acuity and crowding. Such factors delineate key benchmark phenomena that are mostly related to the absolute position of each individual letter within the string. In this respect, the present results indicate a general facilitation in correctly detecting the outer letters of the string, which was particularly pronounced for the first position, in line with several previous studies (e.g., Aschenbrenner et al., 2017; Scaltritti & Balota, 2013; Tydgat & Grainger, 2009). Additionally, we observed a markedly less accurate performance for the central position, a finding that has been associated with the detrimental effects of the backward mask (Castet et al., 2017). Taken together, the present results are roughly in line with the serial position functions generally obtained with more traditional tasks (e.g., Reicher-Wheeler paradigm).

In addition to a successful replication of previous findings, we observed a consistent contextual facilitation for letters in positions 2 and 4 of a five-letter string. This result supports the hypothesis that letter co-occurrences affect a rather early stage of pre-lexical processing. Nevertheless, the exact locus of such facilitation could be further qualified. In fact, co-occurrences could interact with single-letter processing, by boosting individual elements (consistently with some recent neuroimaging evidence, e.g., Heilbron et al., 2020), but also pertain to whole-string processing, thus affecting the integration of letter-level information and higher-order units. The task adopted in Experiment I, which focused on single-letter manipulations but emphasized a more string-oriented approach, could not disentangle between the two alternatives.

A second methodological aspect worthy of consideration is the lack of time-response constraints. Particularly, leaving the two string alternatives available on screen until response could have twofold implications on our results. Firstly, participants could have engaged in post-perceptual decision processes, thus contaminating the effects of interest. Secondly, long processing times prevent us from fully addressing whether contextual information interacts with the allocation of attentional resources, a mechanism of paramount importance in early orthographic processing in general, and first letter advantage in particular (as postulated in, e.g., Aschenbrenner et al., 2017).

Experiment II aimed at replicating the contextual facilitation observed in Experiment I, while taking into account these observations. We introduced a response-time constraint, to attenuate any effect of post-perceptual processes. Moreover, participants were subjected to two different tasks, involving the same materials: a more traditional Reicher-Wheeler task that unambiguously focused on single letter processing, and a Same-Different matching, with a more pronounced emphasis on whole-string processing.

5.5 Experiment II: Materials and Methods

Participants

Sixty-one Italian skilled readers (15 males; age: M=25.34, SD=3.53; 6 left-handed) participated in the experiment. They all respected the same criteria as Experiment I (normal or corrected-to-normal vision, no history of linguistic or neurological impairment), and gave their written informed consent for the study, which was approved by the SISSA Ethics Committee.

Materials

The stimulus set was identical to Experiment I. For the Reicher-Wheeler task, the two options were obtained by presenting only the central letter in the triplet (i.e., for **MBL**SD, the alternatives would have been **B** and **C**, as MCL was the distractor triplet for MBL). In the case of the Same-Different task, the probe was always the five-letter string with the contextual manipulation;

different trials adopted the distractor strings from Experiment I.

Apparatus

The apparatus was identical to Experiment I.

Procedure

Consistently with the previous experiment, a four-point calibration and validation procedure was performed at the beginning of each task, until validation error was below 1° of visual angle in average.

Trials for all tasks began with two black vertical bars indicating the center of the screen (Figure 5.3); the bars substituted the solid dot from Experiment I to reduce perceptual load. Participants were asked to continuously fixate the center for 200 ms to elicit the appearance of the probe. The vertical bars became green whenever the participant's gaze was correctly directed towards the center of the screen, and turned red to indicate an incorrect position. As in Experiment I, extra calibrations and validations were performed each time participants did not succeed in holding the correct gaze position. All tasks included one example, ten practice trials and three pauses. Calibration and validation were performed anew before resuming the experiment at the end of each break.

Reicher-Wheeler Task Probe strings were presented for 100 ms, and were then substituted with a string of five hash marks. After 500 ms, two single-letter options appeared on screen, positioned vertically at $-2.2°$ and $+2.2°$ from the center of the screen, and horizontally located to cue one of the five positions (Figure 5.3A). The options stayed on the screen for 2500 ms, or until response. Consecutive trials were separated by a jittered interval of 1000 ms.

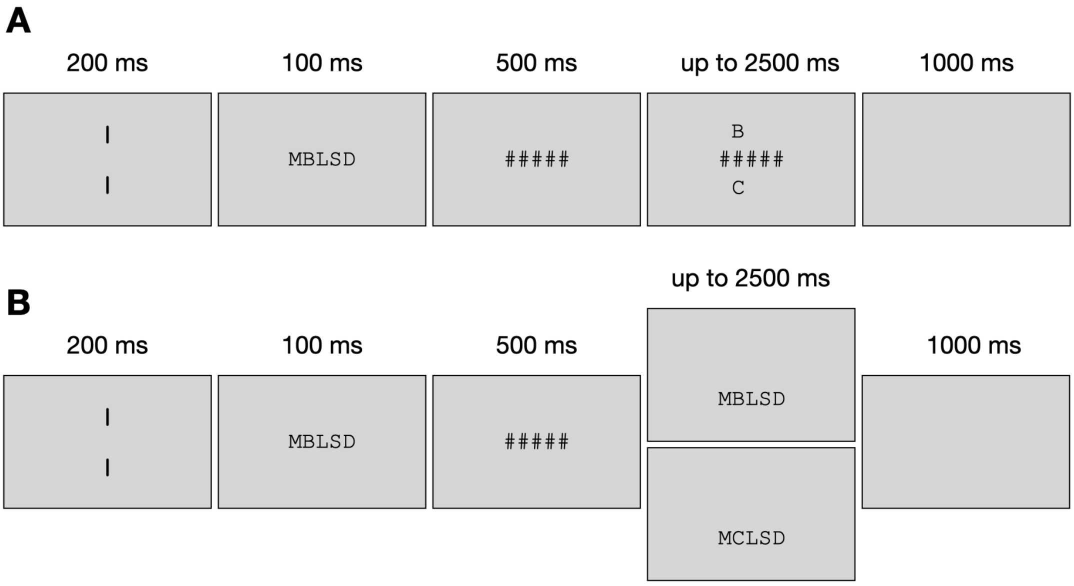


Figure 5.3: Experimental procedures adopted in Experiment II. (A) Reicher-Wheeler Task timeline; (B) Same-Different Task, showing an example for both *same* (upper example) and *different* (lower example) probe-target pairs.

Same-Different Task Probe strings were presented for 100 ms, and then backward masked with a string of hash marks (500 ms). A five-letter target would then appear below the probe position ($-2.2°$ from center) and remain on screen until response, for a maximum of 2500 ms (Figure 5.3B). The inter-trial interval was set to 1000 ms (jittered).

Data Analysis

We followed the same analysis protocol of Experiment I. The introduction of a response timeout allowed us to model, in addition to accuracy, reaction times for correct responses. This analysis was performed via linear mixed-effects models with crossed random intercepts for subjects and trials (Baayen et al., 2008), as implemented in *lme4* (Bates et al., 2007). The distributions of reaction times were investigated and normalized separately for each task, on the basis of the lambda values resulting from independent Box-Cox tests (Osborne, 2010) as implemented in the *MASS* library (Ripley et al., 2013).

For both tasks, no-response trials (Reicher-Wheeler Task: 1.180%, Same-Different: 0.319%) and anticipatory responses of less than 200 ms (Reicher-Wheeler Task: 0.90%; Same-Different: 0.131% of the respective totals) were removed. Inclusion criteria for individual participants were adapted to each task independently. One subject had an overall accuracy of 50% and was excluded from further analyses in the Reicher-Wheeler task; no subject was excluded from the analysis of the Same-Different task.

5.6 Experiment II: Results

Reicher-Wheeler Task

Accuracy The general analysis of all trials included the significant effect of trial order (χ^2=10.285, p<0.001), which suggests that participants became more accurate throughout the experiment. A significant main effect of Position (χ^2=206.719, p<0.001) was further explored via post-hoc comparisons, revealing a strong first letter advantage with responses for the leftmost position being significantly more accurate than for all the other positions (Table A.1).

The analysis of the trials with the contextual manipulation showed no effect of Context (χ^2=0.141, p=0.707), Position (χ^2=0.140, p=0.707), nor of their interaction (χ^2=0.098, p=0.753). Figure 5.4 illustrates both patterns of results.

Reaction Times The analysis of the log-transformed reaction times for correct responses (72.20% of the total) indicated that both trial order (χ^2=58.95,

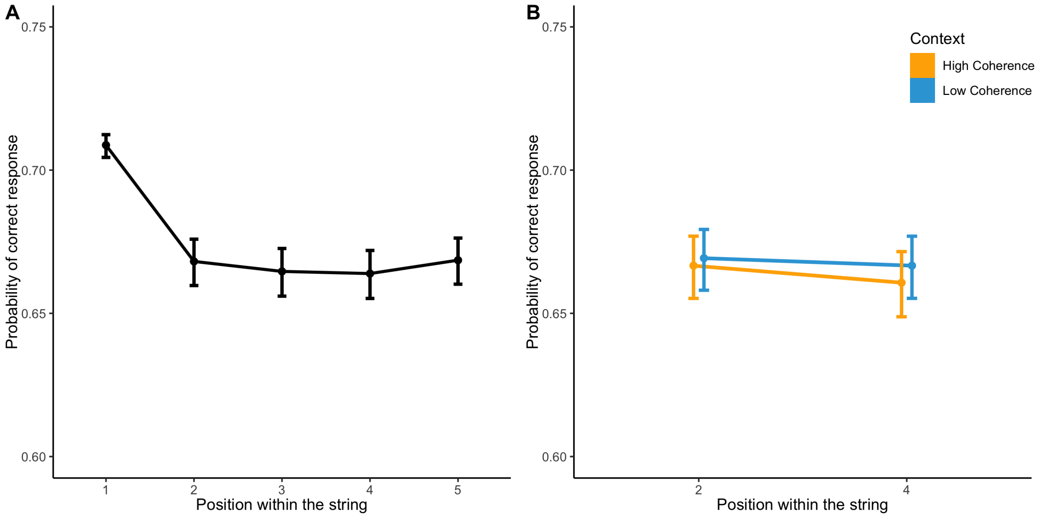


Figure 5.4: Model estimates for probabilities of correct responses in the Reicher-Wheeler Task (A) across all positions and (B) for position 2 and 4, as modulated by context in Experiment II. Error bars represent 95% confidence intervals.

p<0.001) and reaction times on the previous trial (χ^2=45.10, p<0.001) had a significant effect. Crucially, a main effect of Position (χ^2=516.06, p<0.001) complements the pattern observed in the accuracy analysis, with faster responses elicited by the first position within the string. Post-hoc comparisons (Table A.2) revealed a smaller but significant advantage for the last letter over the two crowded positions (5 vs. 2: χ^2=−4.875, p<0.001; 5 vs. 4: χ^2=−3.267, p=0.009). As a result, and in line with previous studies, the serial position function for reaction times in this task is nicely M-shaped (Figure 5.5, panel A).

The analysis of the trials of interest (illustrated in Figure 5.5B) reveals again no effect of Context (χ^2=0.921, p=0.337), nor an interaction between Context and Position (χ^2=1.685, p=0.194). The effect of Position alone was instead marginally significant (χ^2=3.859, p=0.049).

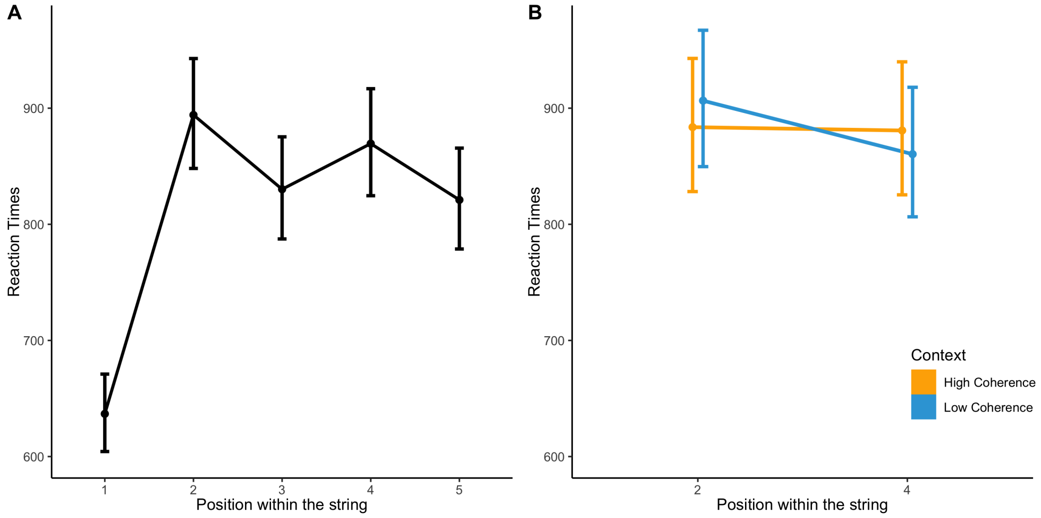


Figure 5.5: Model estimates of reaction times (in milliseconds) for correct responses in the Reicher-Wheeler Task (A) across all positions and (B) for position 2 and 4, as modulated by context in Experiment II. Error bars represent 95% confidence intervals.

Same-Different Task

Accuracy *Same* trials yielded an overall accuracy of 83.4% across subjects, which was not affected by absolute position within the string (χ^2=2.400, p=0.662), nor, in the target trials, by either Context (χ^2=0.162, p=0.686), Position (χ^2=0.235, p=0.627) or their interaction (χ^2=0.002, p=0.964; Figure 5.6A).

Different trials elicited less accurate responses overall (63.6%), which were modulated by the absolute position within the string (χ^2=235.346, p<0.001; Figure 5.7A), associated with a strong first position advantage (Table A.3). Once again, the trials of interest for the contextual manipulation did not show any significant effect of interest (Figure 5.7B; Context: χ^2=0.652, p=0.419; Position: χ^2=1.528, p=0.216; Context x Position: χ^2=0.037, p=0.847)

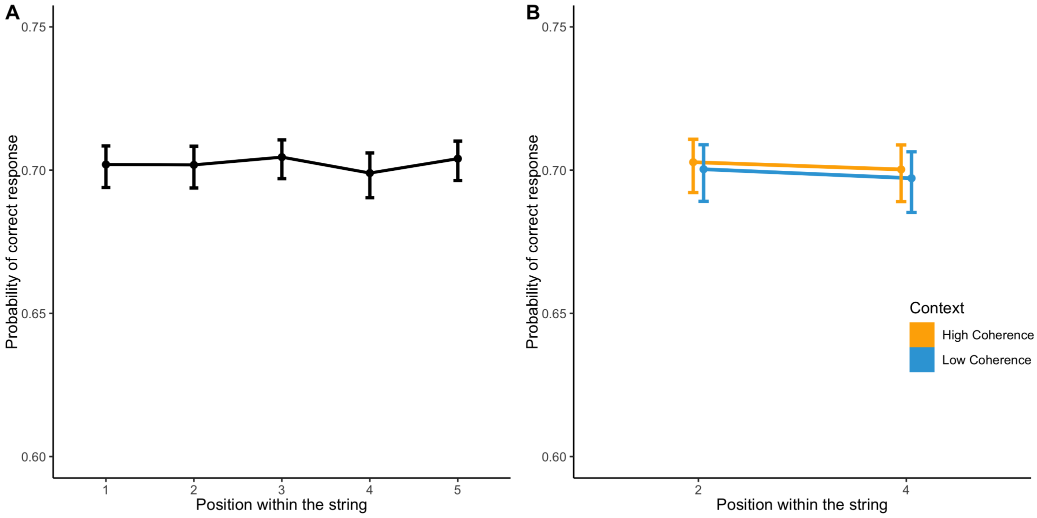


Figure 5.6: Model estimates for probability of correct responses in *same* trials (A) across all positions and (B) for position 2 and 4, as modulated by context in Experiment II. Error bars represent 95% confidence intervals.

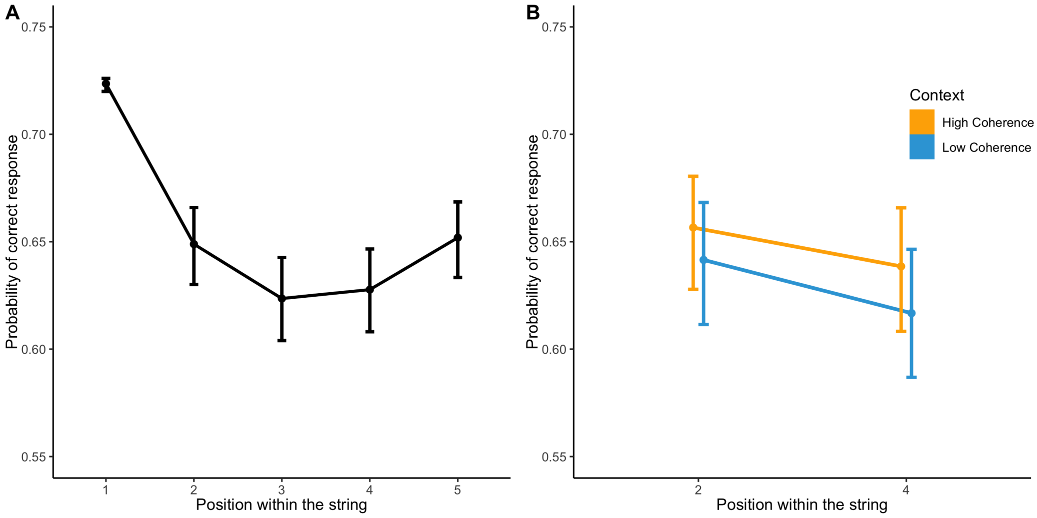


Figure 5.7: Model estimates for probability of correct responses in *different* trials (A) across all positions and (B) for position 2 and 4, as modulated by context in Experiment II. Error bars represent 95% confidence intervals.

Reaction Times The analysis of the inverse-transformed reaction times for correct *same* responses showed main effects of reaction times on the preceding trial (χ^2=163.531, p<0.001) and trial order (χ^2=24.981, p<0.001), but it was not affected by absolute position within the string (χ^2=1.265, p=0.867; Figure 5.8A).

Trials exhibiting a contextual manipulation showed a significant main effect of Condition (χ^2=5.385, p=0.020) and of its interaction with Position (χ^2=7.277, p=0.006; Figure 5.8B). The main effect of Position did not reach significance (χ^2=3.320, p=0.068). Post-hoc comparisons (Table 5.3) revealed that highly coherent triplets elicited faster reaction times for *same* trials, but only for the second position within the string. The opposite effect in position 4 did not reach significance.

Contrast	**Estimate**	**Std. Error**	**t-ratio**	**Pr(>| t |)**	
Position 2					
Low vs. High Coherence	0.0001	0.0000436	2.320	0.026	*
Position 4					
Low vs. High Coherence	-0.0001	0.0000438	-1.512	0.139	

Table 5.3: Context x Position Interaction, Post-hoc Comparisons (Experiment II).

Different trials showed also for reaction times a facilitatory effect for outer positions (main effect of Position: χ^2=535.087, p<0.001; Post-hoc comparisons are reported in Table A.4). The analysis of the trials of interest, however, did not show any significant effect of Context (χ^2=0.0031, p=0.955), while position 2 elicited on average faster reaction times compared to position 4 (χ^2=5.754, p=0.016). The interaction factor did not reach significance (χ^2=2.267, p=0.132; Figure 5.9, panel B).

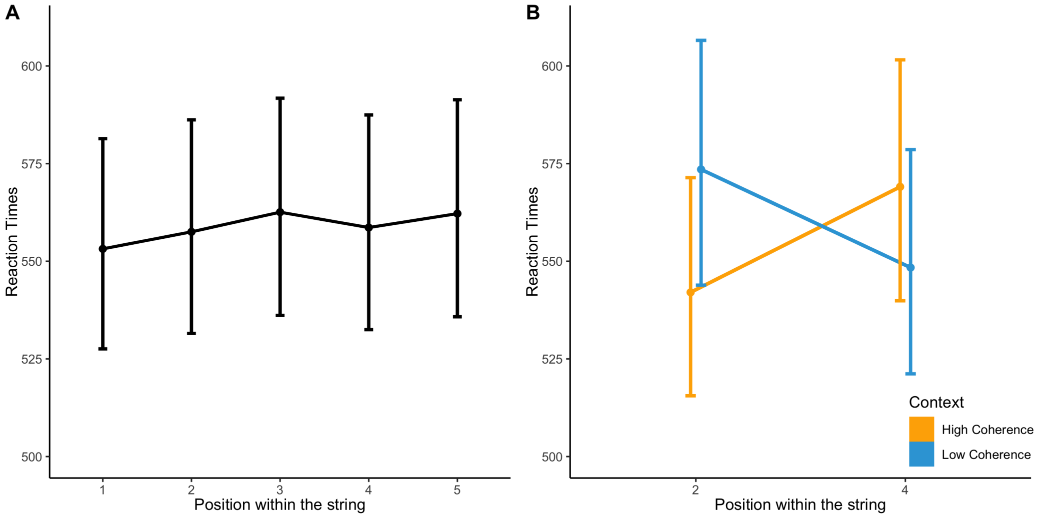


Figure 5.8: Model estimates of reaction times (in milliseconds) for correct responses in *same* trials (A) across all positions and (B) for position 2 and 4, as modulated by context in Experiment II. Error bars represent 95% confidence intervals.

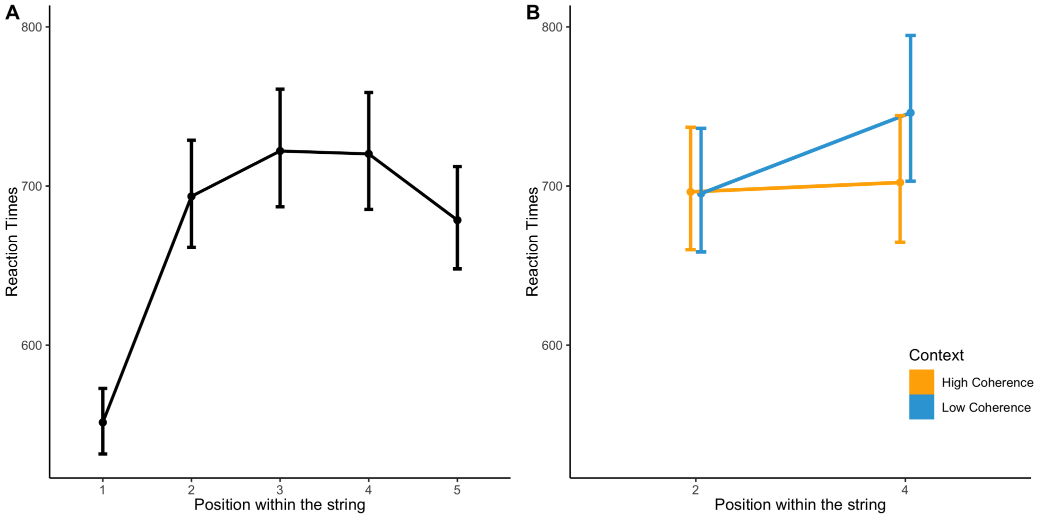


Figure 5.9: Model estimates of reaction times (in milliseconds) for correct responses in *different* trials (A) across all positions and (B) for position 2 and 4, as modulated by context in Experiment II. Error bars represent 95% confidence intervals.

5.7 Experiment II: Discussion

Experiment II further explored the facilitatory effect of letter co-occurrences observed in Experiment I. Skilled readers were presented with five-letter-long stimuli and were then subjected to (i) a two-alternative forced choice with individual letters and (ii) Same-Different matching. In both tasks, participants had limited time to prompt their responses, so that post-perceptual, decisional processes could be attenuated. Consistently with Experiment I, highly coherent triplets (e.g., M**B**L) elicited a facilitatory effect compared to less coherent ones (i.e., P**B**G). However, such effect only surfaced as faster reaction times for *same* judgments in the Same-Different matching task; moreover, the effect was limited to the leftmost part of the string (i.e., position 2 vs. position 4).

Experiment II clearly indicates that the role of contextual information is modulated by task demands. Results from the Reicher-Wheeler task did not yield any effect of letter co-occurrence statistics, suggesting that supra-letter information might be discarded when the paradigm encourages participants to focus on individual letters (Aschenbrenner et al., 2017; Scaltritti & Balota, 2013). On the other hand, the picture emerging from the Same-Different task is more complex. Matching tasks allow to tap into higher level units, notwithstanding a clear distinction between the processes involved in *same* and *different* trials. While *different* judgments trigger a comparison that is based on an analytic, self-terminating search, *same* responses are postulated to engage a more holistic type of process, which also accesses the available higher level information (Barron & Pittenger, 1974). Consequently, the results hereby observed in *different* trials closely resemble the pattern emerging from the Reicher-Wheeler task, and it is in the *same* judgments that we could appreciate a top-down effect of the context in which letters were placed. These findings thus suggest that letter co-occurrence regularities interact with the integration of letter-level information within whole strings, rather than boosting single letter identification *per se*.

The introduction of time constraints did not annihilate the effect of letter co-occurrence statistics, suggesting that this pattern cannot be completely ascribed to decisional processes. However, we observed that letter co-occurrence statistics had a significant effect only for the second position of a five-letter long string. This pattern is nicely in line with the copious evidence indicating that speakers of left-to-right languages (such as Italian, as in the present study) might benefit from an advantaged processing of the leftmost part of orthographic stimuli, from sequences of consonants (e.g., Tydgat & Grainger, 2009) to words (e.g., Scaltritti & Balota, 2013). Enhanced task demands (as adopted in Experiment II) could have resulted in a stronger interaction between such prototypical allocation of visuo-spatial attention (as postulated in Aschenbrenner et al., 2017) and the statistical knowledge of the orthography at hand. Speculatively, more stringent time constraints could have induced participants' attention to be quickly allocated to the beginning of the string, and there captured by a cohesive, consistent group of letters.

Taken together, Experiment II seems to confirm that the statistics of letter co-occurrence in the natural language affect the early stages of string processing. Such an effect is conditional on the task performed, as it requires a more holistic process rather than focusing on individual letters, and it interacts with visuo-attentional resources that are typically deployed in orthographic processing. These considerations suggest the contextual facilitation hereby reported to be genuinely orthographic in nature. Nevertheless, such an effect could be conceived to transcend orthographic information *per se*: individual letters are indeed extremely familiar visual objects, with rather consistent low-level visual features. As a result, letter chunks could be regarded as mere combinations of lower-level objects that result in a consistent visual pattern. In this eventuality, the brain's pervasive sensitivity to statistical regularities could capture and exploit high TP triplets by means of visual statistical learning mechanisms, and beyond any orthographic information. Experiment III was designed to provide insights in this direction, and ascertain the orthographic nature of the contextual facilitation. We adopted the same material as in Experiments I and II, and ran a new Same-Different task. Critically, the strings of stimuli were here rendered as pseudo-characters from the BACS-2 font (C. Vidal & Chetail, 2017). BACS-2 characters are individually paired with characters of the Latin alphabet, so that they exhibit type, number and configuration of strokes (as defined in Changizi et al., 2006), as well as size, junctions, terminations and presence (or absence) of symmetry. This careful construction allows BACS-2 symbols to retain the lower-level characteristics of Roman letters, while disrupting their abstract identities. Any contextual effect would here suggest the recruitment of purely visual resources, engaging the process of co-occurrences between letter features rather than letters; alternatively, a lack of facilitation would confirm the genuine linguistic nature of the effects observed in Experiment I and II.

5.8 Experiment III: Materials and Methods

Participants

The same sixty-one participants that took part in Experiment II were recruited for Experiment III.

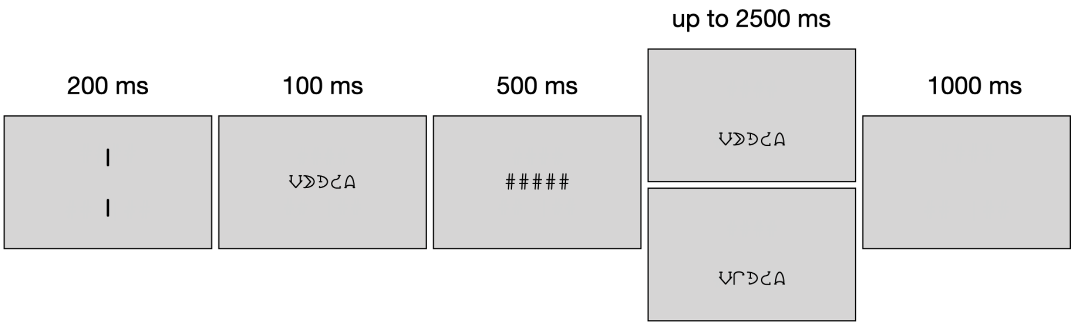


Figure 5.10: Experimental paradigm adopted in Experiment III, showing examples of both *same* (above) and *different* (below) probe-target pairs for the pseudo-character strings.

Materials

The stimulus set was identical to Experiments I and II. Each letter was rendered as a pseudo-character from the BACS-2 font (C. Vidal & Chetail, 2017), thus controlling for the low-level visual aspects of the presentation.

Apparatus

The apparatus was identical to Experiments I and II.

Procedure

The procedure was the same as in Experiment II; a schematic illustration, with examples for the pseudo-character stimuli, is available in Figure 5.10.

Data Analysis

The analysis approach was identical to Experiment II. In the interest of a direct comparison with the key results obtained from Experiment II, non-significant effects were further explored through Bayes Factor (BF) analyses (Dienes, 2014) as implemented in the R package *BayesFactor* (Morey et al.,

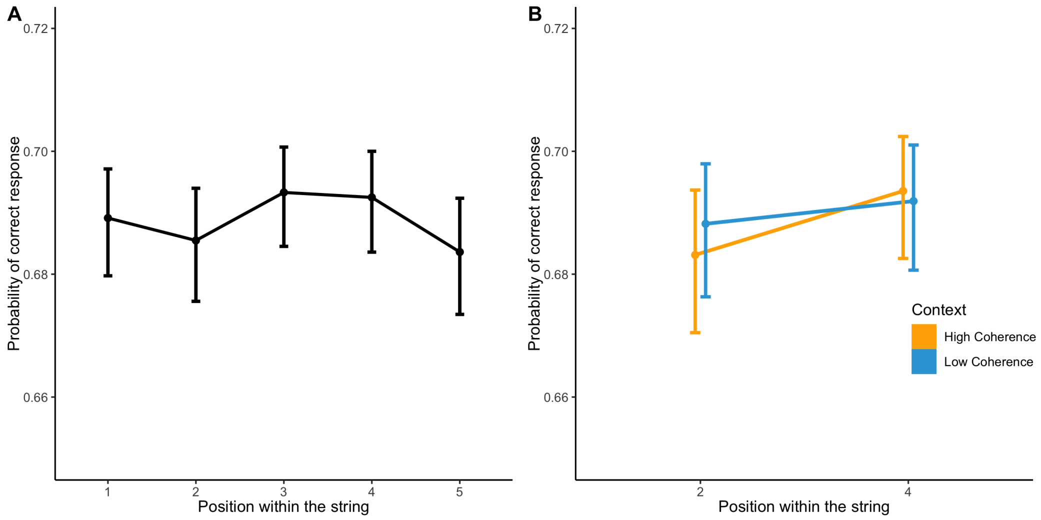


Figure 5.11: Model estimates for probabilities of correct responses in *same* trials (A) across all positions and (B) for position 2 and 4, as modulated by context in Experiment III. Error bars represent 95% confidence intervals.

2015). In particular, the preferred model (that is, the one expressing the hypothesis under study) was compared against models without the effects of interest, thus providing quantifiable evidence in support of H1 or H0 (M. D. Lee & Wagenmakers, 2014).

No-response trials (0.450%) and anticipatory responses of less than 200 ms (0.073%) were removed; no participant was excluded from further analyses.

5.9 Experiment III: Results

Accuracy *Same* trials yielded an overall accuracy of 76.94% across subjects. The statistical effect of absolute position on correct same responses did not reach significance (χ^2=8.705, p=0.069). The analysis of the trials of interest did not reveal any significant effect (Context: χ^2=0.679, p=0.409; Position (χ^2=0.407, p=0.523; Context x Position: χ^2=0.617, p=0.432; Figure 5.11).

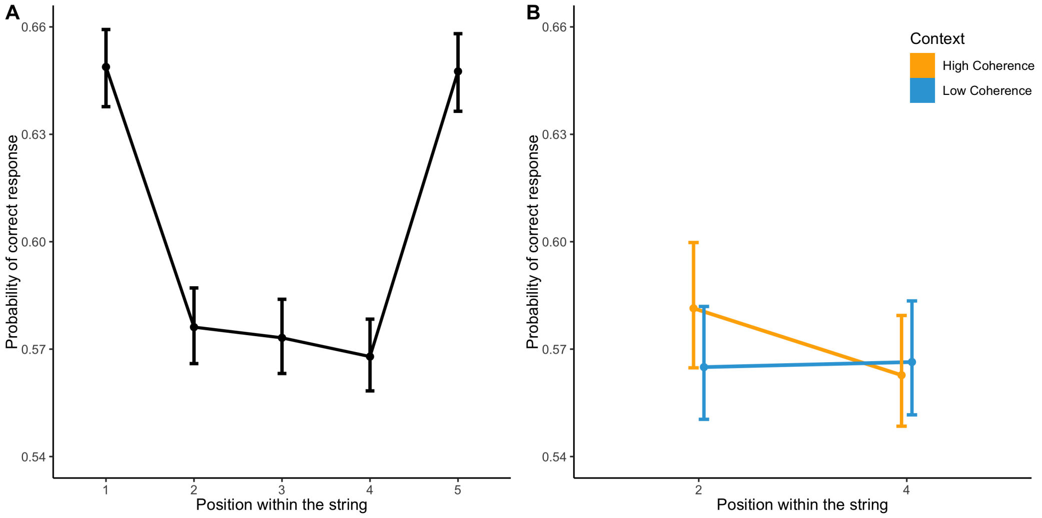


Figure 5.12: Model estimates for probabilities of correct responses in *different* trials (A) across all positions and (B) for position 2 and 4, as modulated by context in Experiment III. Error bars represent 95% confidence intervals.

Different trials elicited markedly less accurate responses (42.33%). Accuracy was modulated by absolute position (χ^2=314.286, p<0.001), with outer positions eliciting more accurate responses (Figure 5.12A; post-hoc comparisons, Table A.5). The analysis on the trials of interest did not indicate any solid effect of Context (χ^2=2.783, p=0.095), Position (χ^2=0.023, p=0.878) or their interaction (χ^2=2.106, p=0.147; Figure 5.12B).

Reaction Times Log-transformed reaction times for correct *same* responses were significantly affected by reaction times on the preceding trial (χ^2=241.790, p<0.001) and trial order (χ^2=60.342, p<0.001), but no significant effect was associated with absolute position within the string (χ^2=1.672, p=0.795; Figure 5.13A). Consistently, trials containing the contextual manipulation were not affected by Position (χ^2=0.921, p=0.337), nor by the interaction between Position and Context (χ^2=1.313, p=0.251). The main effect of Context indicates the presence of a trend, but did not reach statistical significance (χ^2=3.589,

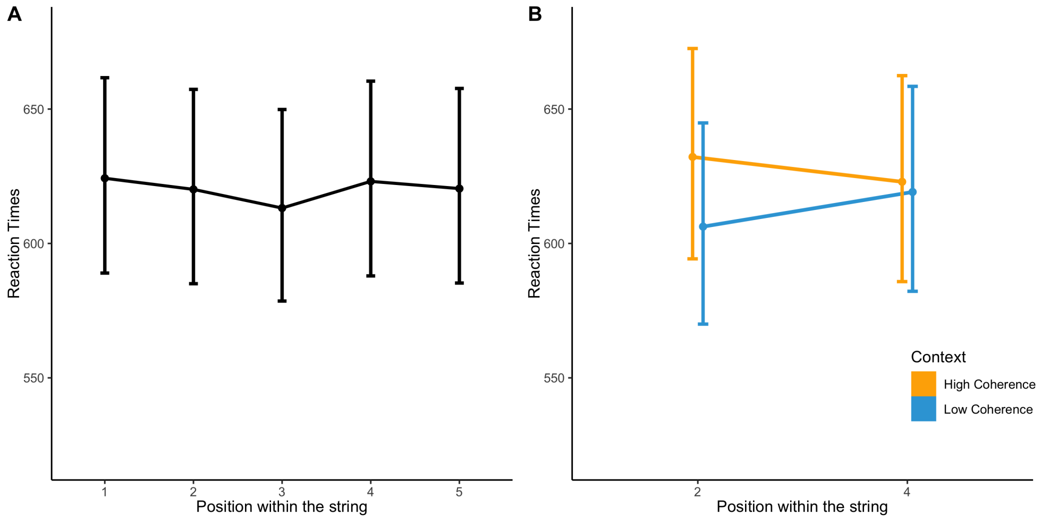


Figure 5.13: Model estimates of reaction times (in milliseconds) for correct responses in *same* trials (A) across all positions and (B) for position 2 and 4, as modulated by context in Experiment III. Error bars represent 95% confidence intervals.

p=0.058). These null results were further explored through a Bayes Factor analysis, which provided evidence against the model including an effect of context (0.15±2.63%) as well as of an interaction term (0.10±1.94%).

Log-transformed reaction times for correct *different* trials indicated a significant facilitation induced by outer positions (χ^2=102.673, p<0.001; post-hoc comparisons, Table A.6; Figure 5.14A). The analysis of the trials of interest did not indicate any significant effect related to Context (χ^2=1.572, p=0.209), Position (χ^2=0.754, p=0.384), nor their interaction (χ^2=0.453, p=0.500).

Cross-experiment analysis The results from Experiment III offer no reliable support for effects of Context in strings of pseudo-characters. Nevertheless, the trend emerging in the case of latencies for correct *same* responses might be worth additional consideration. Particularly, *same* trials in Experiment II indicated that letters enjoy a solid contextual advantage, and a direct comparison with the data harvested in Experiment III could shed some light

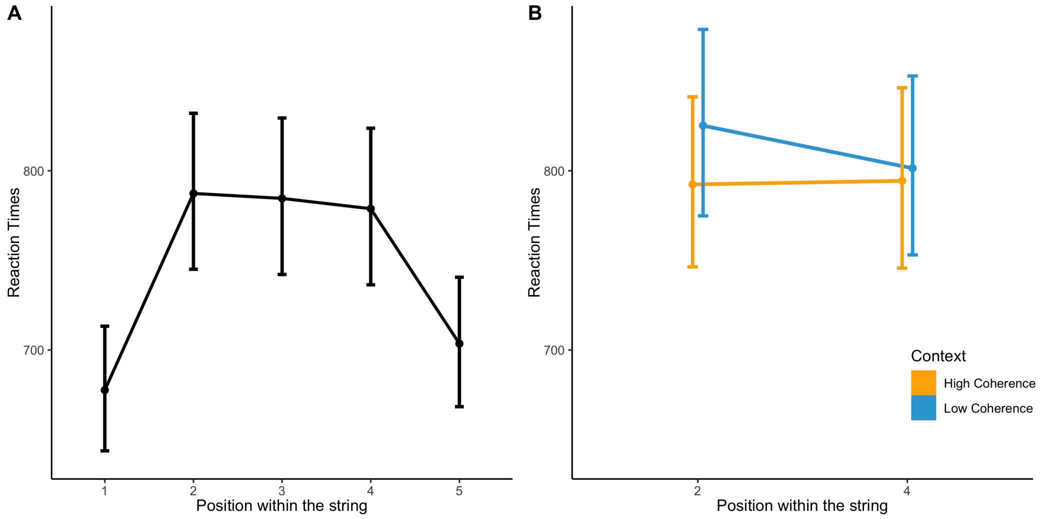


Figure 5.14: Model estimates of reaction times (in milliseconds) for correct responses in *different* trials (A) across all positions and (B) for position 2 and 4, as modulated by context in Experiment III. Error bars represent 95% confidence intervals.

on the locus (visual, or orthographic) of this effect.

We combined the Same-Different data from Experiment II and III, and assessed the interplay of Position (2 vs. 4), Context (high vs. low coherence) and Font (letters vs. pseudo-characters) on reaction times for correct *same* responses. Our results indicate a significant three-way interaction (χ^2=8.580, p=0.003) supporting the fact that statistically coherent contexts affected strings of letters more strongly than strings of visually matched pseudo-characters, specifically for position 2 (Figure 5.15; Table 5.4).

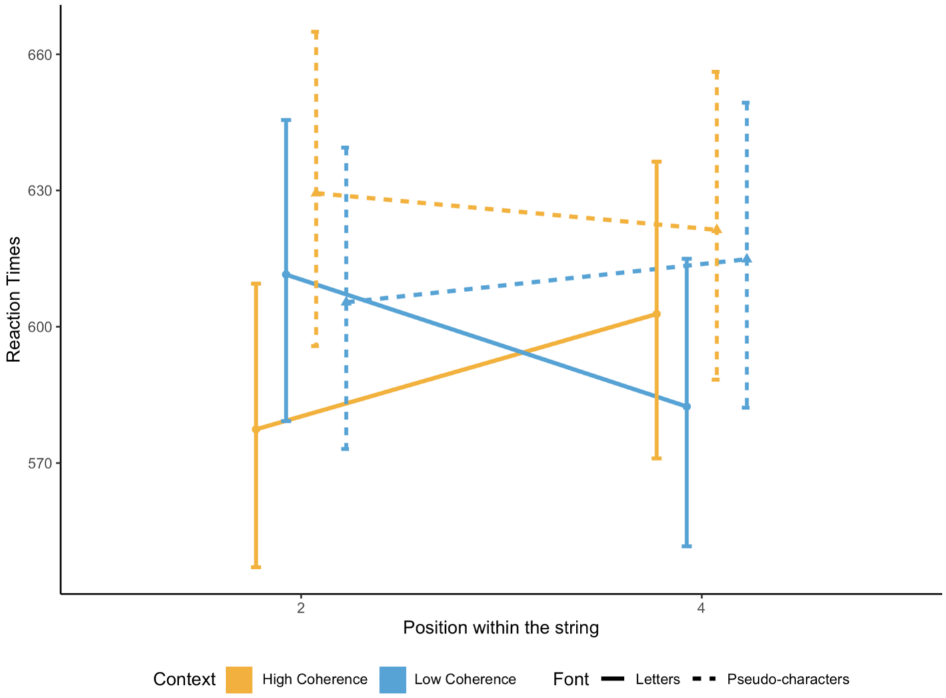


Figure 5.15: Model estimates of reaction times (in milliseconds) for correct responses in *same* trials for position 2 and 4 across fonts, as modulated by context across Experiments II and III. Error bars represent 95% confidence intervals.

5.10 General Discussion

The present study addressed the role of letter co-occurrence regularities in the interaction between visuo-attentional and linguistic processes underlying letter identification. With this aim, we conducted three experiments, in which skilled readers were briefly exposed to strings of five consonants. Crucially, letters in second and fourth position (which are negatively affected by crowding) appeared within either a high or low coherence context, as quantified via transitional probabilities (TP) between adjacent letters in the natural language. Experiment I showed that, when presented with two five-letter alternatives differing by only one letter, skilled readers were significantly more

Position	Context	Estimate	Std. Error	z-ratio	Pr(>| Z |)	
Letters						
2 vs. 4	Low vs. High Coherence	0.091	0.032	2.847	0.004	**
Pseudo-characters						
2 vs. 4	Low vs. High Coherence	-0.028	0.033	-0.860	0.389	

Table 5.4: Font x Position x Context Interaction, Post-hoc Comparisons (Experiments II and III).

accurate in recognizing the correct option when the critical letter appeared in a high TP context. Experiment II further dove into this pattern by having participants perform a Reicher-Wheeler two-alternative forced choice task on single letters, and a Same-Different matching task, which emphasize the processing of individual letters and whole strings, respectively. Moreover, in Experiment II we introduced response-time constraints, thus attenuating any post-perceptual bias. High coherence contexts elicited faster *same* responses in the Same-Different task, but only for letters presented in the second position of the string. In Experiment III participants performed a Same-Different task on the same stimuli, with real letter substituted by their corresponding BACS-2 pseudo-characters (C. Vidal & Chetail, 2017), to disrupt letter identities while preserving their low-level visual features. Here, the contextual manipulation did not yield any significant facilitation.

Taken together, our results indicate that, during the early stages of visual word identification, skilled readers capitalize on their lifelong experience with letter co-occurrence regularities. The effect emerges only when a more holistic processing is encouraged, and with increasing task-demands (e.g., response-time constraints) it interacts with the encoding of positional information for letters within the string. Additionally, this sensitivity to co-occurrences is orthographic in nature, in that it does not emerge with pseudo-characters that preserve the low-level visual features of the string configuration.

While not all letters are equally visible to the reader, contextual information is masterfully exploited to achieve identification. Letter processing draws feedback from higher-level, linguistic knowledge, in a graded pattern of facilitation from fully-fledged words to anagrams and legal, readable pseudowords, all of which provide marked contextual advantages in comparison with illegal strings of consonants, or even isolated presentations (Carr et al., 1979; Prinzmetal, 1992; Reicher, 1969; Wheeler, 1970). Our results are consistent with this graded effect of orthographic familiarity, and indicate that statistically informed, implicitly learned regularities could constitute an intermediate source of feedback, which can support letter processing beyond perceptual bottlenecks. In keeping with evidence involving newly trained items (Huckauf & Nazir, 2007), the present study suggests that implicitly learned patterns, devoid of phonological and semantic connotations, can aid perception, and corroborate the role of learning in overcoming a faulty, excessive integration of features (Pelli et al., 2004).

Our findings pinpoint an effect that has a genuine orthographic component. High transitional probabilities facilitate letter perception when participants engage a holistic process, along the lines of natural reading (as opposed to singling out individual letters, Aschenbrenner et al., 2017; Scaltritti & Balota, 2013), and is conditional on the presence of intact letter identities. Additionally, with shorter response times, statistically coherent contexts advantage targets in the leftmost part of letter-strings. Notably, this positional modulation dovetails with the fact that letters at word onset convey constraining information towards word identity, (Alhama et al., 2019; Clark & O'regan, 1999; Hyönä et al., 1989; McConkie et al., 1989), a crucial notion at the core of some of the most prominent accounts of letter encoding in reading. According to the modified receptive field hypothesis (MRFH, Tydgat & Grainger, 2009), reading acquisition would sharpen visual perception to optimize the encoding of the initial letters of a word (Chanceaux & Grainger, 2012; Chanceaux et al., 2013; Grainger, Bertrand, et al., 2016); here, co-occurrence regularities could be perceived more accurately, and contribute to boost letter identification. Such effect is also consistent with the visuo-spatial account postulated by Aschenbrenner et al. (2017), for which readers would rapidly deploy their attention towards the leftmost letters of the word. Attentional mechanisms could also easily accommodate the role of response-time constraints in our findings: while with unlimited time contextual information can emerge regardless of position (as observed in Experiment I), shorter times constrain this process. Letter information would then be sampled more accurately towards the onset, thus reducing the scope of the contextual advantage to positions close to the focus (Experiment II).

Notwithstanding the orthographic locus of the effect, this contextual facilitation is likely to have a perceptual provenance. Perceptual learning is an implicit mechanism invoked to explain the sharpening of sensory representations following repeated exposure to patterns (Fahle et al., 2002; Gilbert et al., 2001; Goldstone, 1998), an hypothesis that is largely consistent with the numerous statistical learning studies supporting the role of co-occurrence probabilities for the formation of higher-level visual representations (e.g., Fiser & Aslin, 2005; A. L. Lee et al., 2021; Lengyel et al., 2021; Zhao et al., 2014). As a result, co-occurring letter patterns would become familiar to the skilled reader by virtue of an extensive experience with written text, and could provide a source of pre-lexical, visual knowledge for letter and word processing

(Kennedy et al., 2000; Nazir et al., 2004; Nazir & Huckauf, 2007).

The manipulation that led to a contextual facilitation relies on transitional probabilities between adjacent letters, a quantified regularity that has been in the limelight of the statistical learning literature (Aslin et al., 1998; Bogaerts et al., 2016; Endress & Mehler, 2009; Hunt & Aslin, 2001; McDonald & Shillcock, 2003; Pelucchi et al., 2009; Perruchet & Desaulty, 2008; Saffran et al., 1996). The conditional relations between letters were however drawn from the natural language, rather than realized in an artificial lexicon, and resulted in letter chunks that also varied in written frequency. The relation between transitional statistics and chunking has been much debated (for a recent review, see Perruchet, 2019), and arbitrating between the two is beyond the scope of this work. Our results are compatible with a rapid computation of transitional probabilities, informed by previous experience with text, as well as with a chunking mechanism of discrete, frequent units (such as bigrams or trigrams). Importantly, and somewhat beyond advocating for conditional or distributional measures (Thiessen et al., 2013), sensitivity to statistical regularities is here found to mediate and interact with visual and linguistic processes at the core of orthographic processing.

The statistical properties of written input convey pivotal information for skilled readers to exploit during visual word identification, and are indissolubly associated with the ortho-phonotactic rules governing the textual environment. Statistical regularities affect reading behaviors insofar as they are reflective of the distribution of information in a given language (Chetail, 2017). Coherently, sensitivity to distributional properties is likely to interact with the phonological factors at play in letter processing (Winskel et al., 2018), and could have a role in other key benchmark phenomena, such as letter transpositions effects (Johnson et al., 2007; Rayner et al., 2006). A statistical learning perspective could also contribute to our understanding of such phenomena within the context of non-alphabetic orthographies (Gu & Li, 2015; Perea et al., 2010; Velan & Frost, 2009), by quantifying readers' orthographic expectations beyond adjacent relations (Hsu et al., 2014; E. L. Newport & Aslin, 2004; Peña et al., 2002; Perruchet et al., 2004). In conclusion, the present study showcases the potential contribution of statistical learning to our understanding of the early stages of reading, and substantiates the need for models of orthographic processing to account for sensitivity to patterns of regularity in the language (R. Frost, 2012).

Chapter 6

General Discussion

The cognitive system is greatly sensitive to patterns of regularity, which amount to a cornerstone of how the environment is experienced by agents. The textual environment is no exception: with its inherent recurrent structures, the written language offers a cornucopia of regularities to be picked up and capitalized upon by skilled readers. The research included in the present thesis aims at tackling the bond between this pervasive sensitivity to statistical patterns and skilled reading, by asking how statistical learning mechanisms relate to the early stages of visual word recognition.

6.2 Summary of Findings

Among the early processes underpinning word recognition, behavioral and neuroimaging research has extensively investigated the role of morphemes, recurrent letter chunks that convey a fairly regular meaning (e.g., *lead-er-ship*). Skilled readers exhibit a remarkable sensitivity to morphemes; the experiments described in Chapter 2 ask whether such sensitivity might be rooted in visual statistical learning mechanisms. A masked priming lexical decision study assessed the facilitation induced by nonword primes obtained by combining existing stems (e.g., *bulb*) with (i) naturally frequent, derivational suffixes (e.g.,

-ment), (ii) non-morphological, equally frequent word endings (e.g., *-idge*), and (iii) non-morphological, infrequent word endings (e.g., *-kle*). Results indicate that the masked priming induced by nonwords is not modulated by either the frequency or the morphological status of word endings. These findings were successfully replicated in a second experiment adopting a new set of stimuli, featuring morphologically opaque word items (e.g., *flower-flow*) along with the three nonword prime classes. Therefore, morpho-orthographic phenomena as observed in masked priming lexical decision studies cannot be reduced to effects of letter chunk frequency.

Chapter 3 details a study that adopted an FPVS design (Rossion, 2014) and MEG recordings, allowing us to directly compare suffixes and high-frequency endings. By gathering implicit discrimination responses without any task-induced modulation, this paradigm tackled the question of whether suffixes are selectively recognized as meaning-bearing units. Along the same lines, we compared classes of items that could only be distinguished on the basis of a single linguistic feature (such as the presence of letters, readability, familiarity and lexical status), resulting in a tight hierarchy of nested contrasts. By aiming at uncovering which properties can elicit a fast and automatic discrimination, we tackled the very definition of linguistic units in their relevance to skilled reading. Our results reflected the sensitivity of the reading system to form-based regularities, revealing Alphabetic, Readability, Familiarity and Lexicality responses, together with a substantial lack of distinction between suffixes and frequent endings (i.e., a Meaningfulness response). While the adoption of the FPVS technique allowed to gather a direct neural response for different linguistic properties, it is likely to tap into the bottom-up processing of visuo-linguistic material (see also Section 6.4). Coherently, the findings detailed in Chapter 3 do not pinpoint the involvement of higher-level factors, such as phonology and semantics, but instead they shed some new light into the neural underpinnings of skilled reading in relation to perceptual regularities.

Chapter 4 capitalized on the FPVS paradigm to test the emergence of a discrimination response on the basis of the statistical regularities embedded in a presentation stream (an auxiliary hypothesis that emerged from the adoption of the paradigm itself). Skilled readers were passively exposed to sequences of linguistic items with increasing familiarity (i.e., pseudo-characters, strings of consonants, pseudowords and words), presented at a fast rate and periodically interleaved with oddballs. Crucially, each sequence comprised stimuli of the same category, and the only distinction between base and oddball items was the frequency of occurrence of individual tokens within a stream. Frequency-domain analyses revealed robust neural responses at the oddball presentation rate in all conditions, reflecting the discrimination between two locally-emerged groups of items purely informed by token frequency, and regardless of stimulus familiarity. These results provide evidence for a fundamental mechanism of regularity encoding, tuned to frequency of occurrence and potentially underpinning the bootstrapping of linguistic categories.

Chapter 5 focused on early orthographic processing, by asking whether the encoding of letter information within a visual display is affected by letter co-occurrence regularities. Skilled readers were briefly presented with strings of five consonants; critically, letters in position 2 and 4 were embedded in either high (e.g., B in M**B**L) or low (e.g., B in P**B**G) transitional probability (TP) triplets. When presented with two strings differing by the critical letter (e.g., M**B**LSD vs. M**C**LSD, P**B**GVN vs. P**T**GVN), participants correctly identified the right option more often in high-TP than low-TP contexts, regardless of position. A second experiment featured both a Same-Different and a Reicher-Wheeler task with response time constraints, and further qualified the contextual facilitation effect, with high-TP eliciting faster ‘same’ judgements only for letters in position 2. In a third experiment, context had no effect on Same-Different matching with strings of pseudo-characters sharing letters’ low-level visual features. Collectively, the pattern of results emerging from the three experiments indicate that co-occurrence statistics affect the identification and processing of individual letters in tasks that emphasize whole-string processing. This effect is genuinely orthographic, as it is conditional on intact letter identities, and with increasing task demands it only surfaces for letters close to word onset.

6.3 Bundles of Regularity

Language, both oral and written, is a code (Goodman, 1971). Written language unfolds in space, and relies on a structure that is rich in statistical cues: patterns of regularity can be identified in how letters combine into larger units, associated with phonological codes and meanings, and in how these units form words, sentences, discourses. This regular nature potentially provides a precious source of information for the human cognitive system, which is constantly uncovering and capitalizing upon probabilistic regularities. When exposed to a new system, such as an artificial grammar, readers rapidly identify the relevant patterns in the input (e.g., Chetail, 2017; Endress & Mehler, 2009; Lelonkiewicz et al., 2020; Marino et al., 2020; Maye et al., 2008; Maye et al., 2002; Saffran et al., 1996; Saffran et al., 1999; Y. Vidal et al., 2021), a behavior that closely mimics the first encounters of children with the ‘real’ textual environment (e.g., Cassar & Treiman, 1997; Conrad et al., 2013; Pacton et al., 2019; Pacton et al., 2001; Siegelman et al., 2020; Treiman & Kessler, 2021). Similarly, the tacit knowledge of statistical patterns in the written input, reinforced by extensive experience, might support the efficient processing of linguistic material in skilled readers.

Among the possible relevant units in the early processing of visual words, supra-letter, sub-lexical units such as morphemes have been defined as *islands of regularity* (Rastle et al., 2000), in that they combine a rather consistent orthographic form with a specific meaning. As frequently recurring letter clusters with a non-arbitrary form-meaning mapping, morphemes are pivotal units in the written language. Lexica are deeply enriched by morphology, to the point that around 85% of the English words result from inflection, derivation or compounding processes (Algeo & Algeo, 1993; Grainger & Ziegler, 2011). Consequently, morphological units provide a relevant source of regularity for skilled readers to exploit – and an interesting dimension to assess the role of statistically-defined patterns in visual word identification.

The neuroimaging evidence presented in Chapter 3 indicated that suffixes (e.g., *-er*, *-ness*) are not discriminated from meaningless but highly-frequent word endings (e.g., *-el*, *-idge*, which are instead differentiated from non-existent legal letter chunks). Admittedly, this evidence is negative in nature (that is, it comes from a lack of discrimination rather than from the presence of an effect); nevertheless, it was further substantiated by a Bayes Factor analysis with moderate evidence in favor of the Null hypothesis, and provides grounds for further consideration. The result is a characterization of suffixes as frequent letter chunks appearing regularly at the end of words, a definition in keeping with artificial grammar studies. Affix-like units can be carved on the sole basis of their frequency of occurrence (e.g., Lelonkiewicz et al., 2020), and are strongly associated with the appearance in typical positions within larger units (which, in the case of suffixes, is a word-ending position; Crepaldi et al., 2010). Clearly, positional written frequency plays a fundamental role in the very definition of affixes, and constitutes a statistical quantification of morpheme's regularity in form that can successfully support skilled readers in identifying salient morphological units not only in artificial lexica, but also in the real language*, regardless of any form-to-meaning mapping. Importantly however, our findings rely on suffixes presented in isolation. Out of context, suffixes did not alter any stem, and were thus stripped of their morphological function – arguably, they conveyed no meaning. As a result, this statistical definition of suffixes is likely to pertain to an orthographic locus of processing, abstracted away from later, higher-level morphological information.

The masked priming lexical decision study detailed in Chapter 2 complements this picture, by featuring suffixes in the context of semantically opaque words (e.g., *corn-er*) and nonwords (e.g., *corn-ity*). Here, suffixes did not differ from either frequent (e.g., *corn-idge*) nor infrequent (e.g., *corn-og*) letter chunks. This pattern enriches the neural definition of suffixes obtained in the MEG study, by depicting suffixes as *bound* morphemes, subordinated to other, possibly more salient units in morpho-orthographic processing. Such finding fits the predictions of some recent models in the literature, in which the activation of (pseudo-)affix representations is a secondary mechanism that follows the recognition of stems (or, more precisely, edge-aligned embedded words, i.e., *corn* in *corner*, Grainger & Beyersmann, 2017). In light of these combinations, the functional role of morphemes seems to extend beyond the mechanisms of an agnostic, statistically-oriented recognition process. Borrowing a beautiful

---

*Critically, positional frequency of letter chunks is a relatively straightforward quantification of suffixes' form regularity, which can be easily extended to prefixes (that is, affixes appearing at the beginning of a word, e.g., *un-real*). However, the case of non-concatenative classes of morphemes, such as circumfixes (*ge-t* in the past participle of German verbs, such as *gesagt*, *said*) or transfixes (*k-t-b* for *writing* in Arabic) might require a different approach (see, e.g., Finley & Newport, 2021, for a recent discussion on this topic).

image from Baayen et al. (2016): “[…] A pawn by itself has no independent meaning. A pawn on the second row of a chess board can be totally inert, whereas the same pawn on the seventh row, free to promote to a queen, has tremendous potential” (Baayen et al., 2016, p. 24). An exhaustive characterization of morphemic units, and of their relevance in visual word recognition, should include a description of morphemes within the linguistic system, thus capturing the rules that govern derivational and morpho-semantic processes. Whether this complex picture can be rendered via statistically driven patterns of co-occurrences is an open issue for future research (but see, e.g., Amenta et al., 2020; Grainger & Beyersmann, 2020; Marelli et al., 2015; Marelli & Baroni, 2015, for recent evidence in this direction). Nevertheless, a complete depiction of morphemes cannot abstract away from the linguistic system and its constellation of combinations to fully account for morphological processes in visual word identification.

Taken together, these considerations around bound morphemes point towards a fundamental dichotomy. Morphemes are meaning-bearing units, building blocks of the language, as well as orthographic units informed by statistical regularities. From the findings included in the present thesis, these two levels are somewhat separated, in that statistical patterns can reflect salient linguistic structures and support their recognition, however they cannot fully explain the linguistic relevance of such units in visual word processing. Critically, this distinction might be hindered when considering lexical items: words are indeed intrinsically meaningful visual objects, which cannot be deprived of their associations with orthographic, phonological, morphological and semantic information. On the other hand, the focus on sublexical units such as suffixes allows to isolate the relative contribution of form and meaning based regularities, which can provide equally relevant and yet independent contributions in the race towards visual word identification. Through this unique window into skilled reading, it is possible to draw a line between statistical learning and reading, with sensitivity to regularities being mostly recruited during early orthographic processes.

Notably, an orthographic account of statistical learning mechanisms in skilled reading sits well with the localist dual-route model proposed by Grainger and Ziegler (2011), which postulates a fine-grained path, in which co-occurring letter chunks, associated with a precise position within larger strings, feed orthographic representations of multi-letter graphemes and affixes. While Grainger and Ziegler (2011) do not explicitly refer to statistical learning mechanisms (but see Crepaldi et al., 2010, for a discussion on how letter co-occurrences might inform affix representations), it is plausible to associate this early level of processing with skilled readers' familiarity with the statistical regularities of the input. Similarly, the series of experiments enclosed in Chapter 5 indicate that early orthographic processes (such as combining letters into a unique code, beyond perceptual constraints) draw from an implicit knowledge of the statistical structure inherent to the written text (a finding in line with artificial grammar studies, e.g., Chetail, 2017) – even if facilitatory patterns only surface under specific conditions. Once again, the experimental evidence detailed in Chapter 5 pertains a level of processing that is intentionally devoid of higher-level linguistic properties, such as phonology or semantics, and thus corroborates the conclusion that known visual regularities interact with a rather early stage of visual word identification.

In conclusion, the research included herein suggests that the knowledge of the statistical regularities inherent to written input supports early orthographic processes in skilled reading. As a domain-general linchpin of information processing, statistical learning provides a critical interface between visual and linguistic processes (e.g., Y. Vidal et al., 2021), in line with a recruitment (or recycling, Dehaene et al., 2005) of cognitive resources not originally deputed to reading. The extensive experience with visual regularities would guide the recognition of statistically cohesive visual patterns, which in turn become potential candidates for the relevant functional units in the language (such as morphemes or graphemes). Outside of the realm of form regularities, and beyond identification, chunking or bootstrapping, other linguistic processes would then require the involvement of higher-level knowledge. Therefore (and somewhat speculatively), the involvement of statistical learning mechanisms is limited to a set of early processes amounting to part of the mechanisms leading to visual word identification.

6.4 Looking Through a Prism: Methodological Notes

The statistical regularities under study were extracted from the written language, and thus result in patterns that capture the linguistic structure as it might be experienced by the reader. Compared to the fully-deterministic regularities that populate the artificial grammars in the majority of the statistical learning literature, this approach might be considered more ecological, in a closer approximation to reading processes. Nevertheless, the relevance of such “natural” regularities was assessed in a set of artificial tasks. Therefore, it is important to frame the conclusions drawn from this research within the scope of the experimental techniques and methodologies adopted.

As discussed in Chapters 3 and 4, Fast Periodic Visual Stimulation paradigms (FPVS, Rossion, 2014) target automatic and implicit neural discrimination phenomena by means of a rapid and periodic stimulation. The response of interest is not elicited by a task, and emerges without any direct or explicit engagement with the material. Additionally, the items are presented sequentially and with a sinusoidal modulation of spatial contrast, in a fast presentation rate (in the case of our studies, 6 Hz). The FPVS designs adopted in these studies are thus likely to tap into rather early stages of processing, possibly dominated by bottom-up, visual information rather than by top-down, higher level linguistic factors.

This consideration can be easily extended to the experiments included in Chapter 5. Here, unreadable consonant strings, with no connections to phonological or semantic information, were presented briefly, and then immediately masked before the administration of one of three tasks, all of which are assumed to pinpoint early orthographic processes. The two-alternative forced choice task with whole strings has been critical in the study of letter processing, by fostering new insights into the parallel identification of individual letters in words (e.g., Adelman et al., 2010), as well as the mechanisms at the basis of the first-letter advantage phenomenon (e.g., Aschenbrenner et al., 2017; Scaltritti & Balota, 2013). Comparably, Reicher-Wheeler two-alternative forced choice tasks (Reicher, 1969; Wheeler, 1970) can be adopted to study early processes that draw heavily on short-term visuo-spatial and attentional resources, along the lines of other partial report techniques (e.g., Averbach and Coriell, 1961; see Castet et al., 2017 for a recent critical review). Lastly, Same-Different matching tasks have been generally considered to tap into early, pre-lexical processing of order encoding (e.g., Angiolillo-Bent & Rips, 1982; Kinoshita & Norris, 2009; Perea & Acha, 2009), and have been extensively adopted to study the encoding of visual material beyond arrays of letters and pseudo-characters (as reviewed in, e.g., Proctor, 1981; Van Zandt et al., 2000).

Chapter 2 features the adoption of a masked priming design, in line with the numerous studies adopting subliminal displays to probe mechanisms of visual word processing (Forster, 1998; Masson & Bodner, 2003; Van den Bussche et al., 2009). Critically, this technique can tap into several stages of processing (Kinoshita & Lupker, 2004), mostly depending on the parameters governing the presentation of the prime (i.e., prime duration and visibility M. H. Davis & Rastle, 2010; Van den Bussche et al., 2009). The display of primes below conscious appreciation, combined with lexical decision tasks (Forster & Davis, 1984) has been pivotal in addressing morpho-orthographic processes during visual word identification (Rastle & Davis, 2008), in an early stage that is largely free of semantic influences (as observed in, e.g., Giraudo and Voga, 2016; Longtin and Meunier, 2005; Tseng et al., 2020; but refer also to, e.g., Feldman and Basnight-Brown, 2008; Feldman et al., 2012 for a different perspective, and to M. H. Davis and Rastle, 2010; Feldman et al., 2009 for a debate around this topic). The emergence of higher-level, semantic effects can be more easily captured with different tasks (e.g., Amenta & Crepaldi, 2012; Duñabeitia et al., 2011; Marelli et al., 2013), independently of any sensitivity to morpho-orthographic structure or, more generally, to the factors that typically affect the early stages of visual word identification. Conversely, the study presented in Chapter 2 intentionally aimed at tapping into an earlier mechanism, which prompted the choice of a masked priming lexical decision with carefully controlled experimental parameters (50 ms and 42 ms prime duration for Experiments I and II, respectively). Notably, the pattern of results observed did not show any effect of interpretability or morpheme interference, in keeping with our design.

In sum, our findings suggest an involvement of statistical learning mechanisms in the early stages of visual word processing; however, they consistently stem from studies that principally tap into early resources. As already argued, the case of morphological units is emblematic, in that different lenses could reveal a picture that both encompasses and transcends the role of statistical regularities *per se*. Is there a clear separation between visual and linguistic regularities, in the cascade of word processes? How do these levels, orthographic and morphological, statistically-informed and linguistically-driven, interact? Addressing these questions will require future studies to adopt diversified techniques and novel quantification of relevant patterns, thus resulting in a more complete characterization of the mechanisms that govern visual word identification.

A final methodological remark comes from Chapter 4, which showed how novel distributional information can be easily and rapidly acquired even if it departs from the distributions learned over a lifetime, and regardless of stimulus familiarity. This finding falls in line with the extensive literature showcasing the pervasive and ubiquitous nature of statistical learning phenomena. In turn, the results included Chapter 4 call future studies for caution: the cognitive system is constantly, dynamically engaging with the material presented, detecting new regularities; any assessment of pre-existing statistical knowledge could thus be contaminated by newly acquired statistics, hidden in the manipulation and potentially unrelated to the experimental question at hand.

6.5 Conclusions

In the puzzle of skilled reading, human's statistical learning capacities and pattern of regularities in the textual environment are perfectly complementary pieces – an observation that is clearly reminiscent of questions around the origin of language itself. Indeed, sensitivity to statistical cues is a cornerstone of information processing, involved in the more ancestral visual system that also supports reading. The present thesis serves to highlight, and possibly circumscribe, the contributions of statistical learning mechanisms in early visual word recognition processes.

Appendices

Appendix to Chapter 4:
Temporal Evolution of Frequency-Based Discrimination Response

---

The main analysis revealed reported in Chapter 4 reveals a selective neural response to the oddball stimuli demonstrating a discrimination between oddball and base tokens that occurred during the 60-second trial period. As a follow-up analysis, we examined the temporal build-up of this response during the course of the stimulation trial.

It is important to note that this analysis was performed as a post-hoc exploration and was thus unavoidably constrained by the current experimental design. The study's design was not ideally suited to investigate the temporal evolution of the effect for at least two reasons. First, the division of the stimulation trial into smaller epochs was contingent on the principle that frequency resolution is inversely proportional to the duration of the signal, with smaller temporal windows necessarily yielding lower spectral resolutions. This is particularly relevant in the context of the present experiment, where the frequency of interest was manipulated experimentally, and thus sits sharply at 1.2 Hz. With lower frequency resolution, the band including 1.2 Hz unavoidably also includes surrounding frequencies that were not entrained; therefore, signal is confounded by noise. In order to counteract this issue and obtain the steady-state response with the best possible signal-to-noise ratio, we broke each trial into the minimum number of smaller time windows that would allow us to assess a temporal evolution, i.e., two 30-seconds chunks. Certainly, the use of a longer stimulation period could have afforded more subdivisions and would have been more suited to effectively capture the time-course of the response; future studies that aim specifically at testing the temporal evolution of the frequency discrimination signal should definitely adopt this modification.

Second, the extent of the critical frequency-of-occurrence manipulation within each time window likely varied across trials and participants. While in a given 60-second trial the relative frequency-of-occurrence difference of base and oddball tokens was strictly designed to be four to one (i.e., 36 base vs. 9 oddball token repetitions), the corresponding ratio during a given period within the trial was not controlled. This is due to the fact that the presentation order of individual tokens was maximally randomized (for more details, see the Experimental Paradigm and Procedure section in the main text). This allowed us to eliminate the induction of periodic responses other than those related to the base and oddball presentation frequencies (e.g., a response to a specific token appearing periodically every n-th item).

These considerations notwithstanding, we tried to determine whether, even in the present experiment, the frequency-of-occurrence effect would increase as a function of participants' exposure to the statistical structure of the input stream. If so, we would expect the oddball response to be greater in a late, compared to an early, time window along the stimulation period. Bearing in mind that the time evolution analysis would be necessarily noisy, it was important to have a term of comparison. Therefore, we ran the same exact analysis at the base stimulation frequency, that is, we assessed how the entrainment at 6 Hz would change in the first 30 seconds of stimulation vs. the second 30 seconds of stimulation. Because this response is purely perceptual and does not build in any way on the statistics of the stimulation stream, we expected the signal to change less within the stimulation trial. Also, if any change should occur, it would likely go in the opposite direction, that is, a weaker response in the second part of trial, due to perceptual habituation. Finally, since the perceptual entrainment at the base frequency is much stronger than the statistical learning entrainment at the oddball frequency (see the base stimulation frequency results in the main text), we expected this signal to be more resistant to the substantial decrease in frequency resolution, and therefore in signal-to-noise ratio. As a consequence, the time-window analysis on the base response constitutes a further term of comparison for what concerns the statistical significance of the effects.

Data Analysis

EEG data pre-processing was the same as described in the main analysis. This was also the case for the frequency domain analysis except that before the averaged trials were submitted to a Fast Fourier transform (separately for each condition and participant), they were divided into two epochs ranging from 0 to 30 seconds and from 30 to 60 seconds. Furthermore, in each time window the local baseline-correction was adjusted according to the frequency resolution of the epochs in order to be comparable to the one applied to the entire 60-second trial. Specifically, in the main analysis we considered 10 bins on each side of the frequency of interest; at a resolution of 1/60=0.0167 Hz, this corresponds to 0.167 Hz on each side. Since we now have half the resolution (i.e., 1/30=0.0333 Hz), we considered only 5 bins from each side, which covered again 0.167 Hz overall. As in the main analysis, we excluded immediately adjacent bins and bins with minimum and maximum values. Oddball and base responses were defined as the sum of the baseline-corrected amplitudes at the oddball (1.2 Hz) and at the base (6 Hz) stimulation frequencies and their corresponding first three harmonics (oddball: 2.4, 3.6, 4.8 Hz; base: 12, 18, 24 Hz). Responses were calculated over the same regions of interest (ROIs) as the ones reported in Chapter 4: for the oddball response, one predefined occipito-parietal area on the left hemisphere and its analogous on the right hemisphere were used, whereas for the base response, one large occipital parietal area was selected (see Figure 4.2 in the main text).

Results

Participants' individual oddball and base responses across the two time windows are displayed in Figure A.1 for each experimental condition. As it is clearly shown in the figure, participants' oddball responses across the two halves of the stimulation period are rather variable (i.e., left column of Figure A.1). Despite this variability, however, most participants seem indeed to show a stronger oddball response in the second 30-second period of the stimulation trial compared to the first (e.g., in the Word condition, panel A in Figure A.1, 17 out of the 27 participants with an oddball response beyond the noise level lie above the diagonal). This observation is also supported by the descriptive statistics. With the exception of Nonwords, in all other experimental conditions the mean oddball response in the second time window is numerically greater than in the first time window (averaged across ROIs, Words: Time 1=0.042, *SD*=0.10, Time 2=0.074, *SD*=0.07; Pseudowords: Time 1=0.051, *SD*=0.08, Time 2=0.057, *SD*=0.08; Nonwords: Time 1=0.046, *SD*=0.08, Time 2=0.042, *SD*=0.09; Pseudofonts: Time 1=0.021, *SD*=0.08, Time 2=0.033, *SD*=0.08).

In sharp contrast, participants' individual base responses do not show as much variability between the first and second half of the stimulation period; in the right column of Figure A.1, participants are all concentrated close to the diagonal. Furthermore, it appears that for the majority of the participants the base response in the second time window is diminished compared to the first (e.g., in the Word condition, panel A in Figure A.1, 20 out of 29 participants lie below the diagonal). The mean base response in the first and second time window per condition are as follows: Words: Time 1=0.410, *SD*=0.24, Time 2=0.387, *SD*=0.23); Pseudowords: Time 1=0.384, *SD*=0.23, Time 2=0.367, *SD*=0.21; Nonwords: Time 1=0.433, *SD*=0.18, Time 2=0.407, *SD*=0.18; Pseudofonts: Time 1=0.346, *SD*=0.12, Time 2=0.319, *SD*=0.14). The effect of time window and its interaction with the experimental conditions on the base and oddball response was statistically assessed through ANOVAs, with Condition (Words, Pseudowords, Nonwords and Pseudofonts) and Time Window (first and second) as within-groups factors. In the case of the oddball response, the within-groups factor of Hemisphere was also included. Results on the oddball response revealed no significant difference between the first and second time window (F(1,28)=1.491, p=0.232; Time 1: M=0.040, *SD*=0.05; Time 2: M=0.051, *SD*=0.04). In addition, there were no significant interactions involving the effect of Time Window. These statistics indicate that the trends described above do not allow any firm conclusion as to the temporal evolution of the discrimination signal, which surely deserves further investigation in experiments specifically designed to that aim. At the same time, these statistics are clearly not surprising in the context of the current experimental design, given the inherent noise and variability in the measurement of the oddball response within each time window that is discussed above.

Results on the base response revealed a significant effect of Time Window (F(1,28)=15.055, $p<0.01$), with the response in the second time window being smaller than the first time window (Time 1: M=0.393, SD=0.20; Time 2: M=0.370, SD=0.19). There were no significant interactions involving the effect of Time Window.

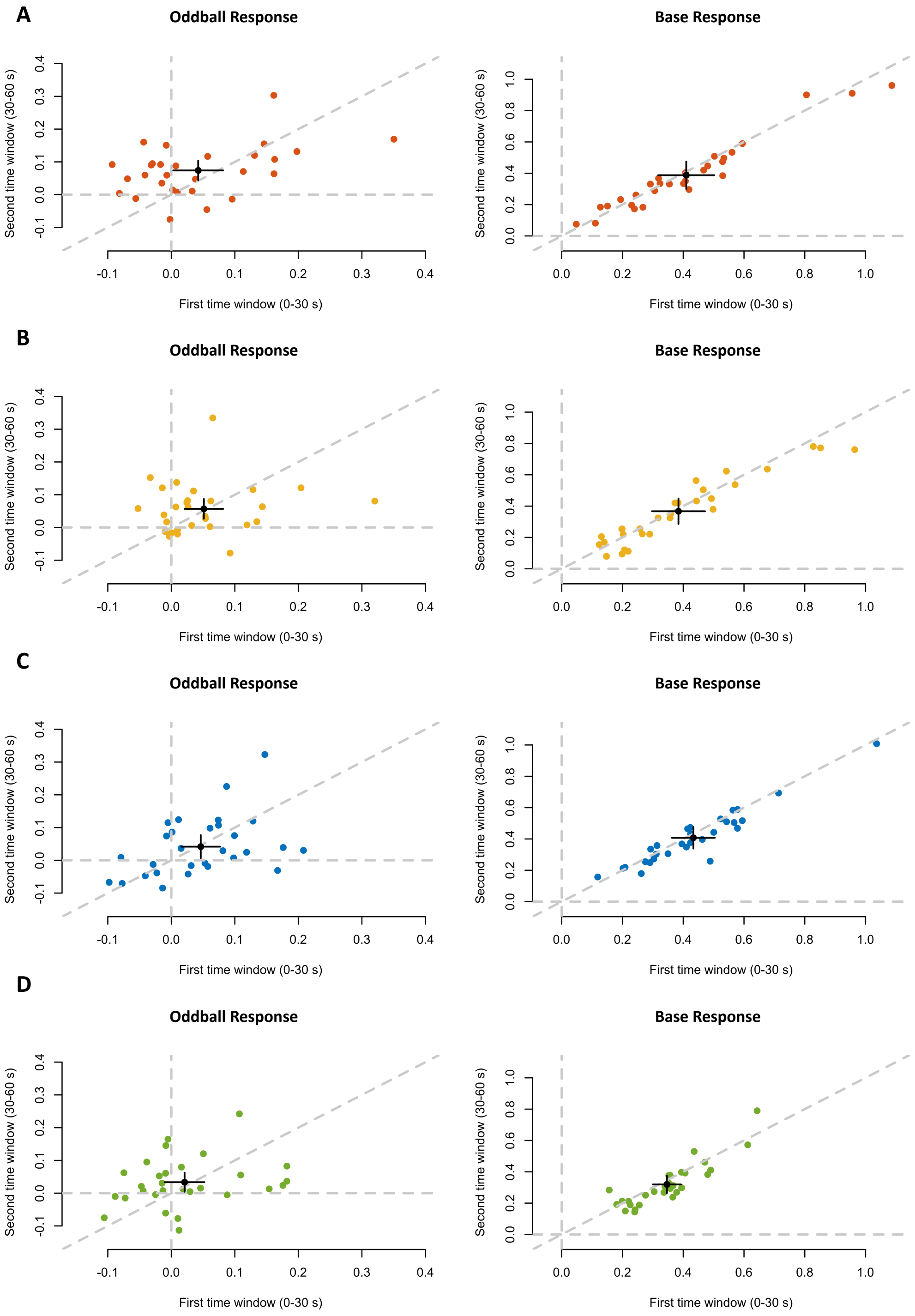


Figure A.1: Temporal evolution of oddball (left column; averaged over left and right ROIs) and base (right column) responses during the stimulation period for Words (A), Pseudowords (B), Nonwords (C) and Pseudofonts (D). In each graph, the x and y axes represent the neural response in the first time window (ranging from 0 to 30 seconds) and the second time window (ranging from 30 to 60 seconds), respectively. Each dot represents an individual participant, while the dotted lines illustrate the level of noise in each time window. The black dot illustrates the mean response in each time window and the error bars denote the corresponding 95% confidence intervals.

Appendix to Chapter 5:

Additional Tables

Positions	**Estimate**	**Std. Error**	**z value**	**Pr(>$\mid z \mid$)**	
2 - 1	−1.24	0.11	−11.54	<0.001	***
3 - 1	−1.31	0.11	−12.26	<0.001	***
4 - 1	−1.33	0.11	−12.40	<0.001	***
5 - 1	−1.23	0.11	−11.45	<0.001	***
3 - 2	−0.07	0.10	−0.76	0.94	
4 - 2	−0.09	0.10	−0.92	0.89	
5 - 2	0.01	0.10	0.10	1.00	
4 - 3	−0.02	0.10	−0.16	1.00	
5 - 3	0.08	0.10	0.85	0.91	
5 - 4	0.10	0.10	1.01	0.85	

Table A.1: Experiment II, Reicher-Wheeler Task, Accuracy: Post-hoc Comparisons across Positions.

Positions	**Estimate**	**Std. Error**	**z value**	**Pr(>| z |)**	
2 - 1	0.34	0.02	19.88	<0.001	***
3 - 1	0.27	0.02	15.51	<0.001	***
4 - 1	0.31	0.02	18.19	<0.001	***
5 - 1	0.25	0.02	14.90	<0.001	***
3 - 2	−0.07	0.02	−4.23	<0.001	***
4 - 2	−0.03	0.02	−1.59	0.50	
5 - 2	−0.09	0.02	−4.88	<0.001	***
4 - 3	0.05	0.02	2.63	0.07	
5 - 3	−0.01	0.02	−0.63	0.97	
5 - 4	−0.06	0.02	−3.27	0.01	**

Table A.2: Experiment II, Reicher-Wheeler Task, Reaction Times: Post-hoc Comparisons across Positions.

Positions	**Estimate**	**Std. Error**	**z value**	**Pr(>| z |)**	
2 - 1	−2.77	0.23	−11.96	< 0.001	***
3 - 1	−3.22	0.23	−13.88	< 0.001	***
4 - 1	−3.15	0.23	−13.57	< 0.001	***
5 - 1	−2.72	0.23	−11.73	< 0.001	***
3 - 2	−0.45	0.20	−2.24	0.16	
4 - 2	−0.38	0.20	−1.88	0.32	
5 - 2	0.06	0.20	0.28	1.00	
4 - 3	0.07	0.20	0.36	1.00	
5 - 3	0.50	0.20	2.53	0.08	
5 - 4	0.43	0.20	2.17	0.19	

Table A.3: Experiment II, Same-Different Task, *Different* trials, Accuracy: Post-hoc Comparisons across Positions.

Positions	**Estimate**	**Std. Error**	**z value**	**Pr(>| z |)**	
2 - 1	0.00037	0.000022	16.55	< 0.001	***
3 - 1	0.00042	0.000023	18.45	< 0.001	***
4 - 1	0.00042	0.000023	18.32	< 0.001	***
5 - 1	0.00033	0.000022	15.16	< 0.001	***
3 - 2	0.000056	0.000024	2.31	0.14	
4 - 2	0.000053	0.000024	2.16	0.19	
5 - 2	−0.00003	0.000024	−1.32	0.68	
4 - 3	−0.000003	0.000025	−0.14	1.00	
5 - 3	−0.000088	0.000024	−3.60	< 0.001	***
5 - 4	−0.000085	0.000024	−3.48	< 0.001	***

Table A.4: Experiment II, Same-Different Task, *Different* trials, Reaction Times: Post-hoc Comparisons across Positions.

Positions	**Estimate**	**Std. Error**	**z value**	**Pr(>| z |)**	
2 - 1	−1.28	0.12	−10.93	<0.001	***
3 - 1	−1.34	0.12	−11.41	<0.001	***
4 - 1	−1.44	0.12	−12.22	<0.001	***
5 - 1	−0.02	0.11	−0.20	1.00	
3 - 2	−0.06	0.12	−0.49	0.99	
4 - 2	−0.16	0.12	−1.37	0.65	
5 - 2	1.25	0.12	10.74	<0.001	***
4 - 3	−0.11	0.12	−0.88	0.90	
5 - 3	1.31	0.12	11.22	<0.001	***
5 - 4	1.42	0.12	12.04	<0.001	***

Table A.5: Experiment III, Same-Different Task, *Different* trials, Accuracy: Post-hoc Comparisons across Positions.

Positions	**Estimate**	**Std. Error**	**z value**	**Pr(>| z |)**	
2 - 1	0.15	0.02	7.54	<0.001	***
3 - 1	0.15	0.02	7.20	<0.001	***
4 - 1	0.14	0.02	6.75	<0.001	***
5 - 1	0.04	0.02	2.15	0.20	
3 - 2	−0.00	0.02	−0.16	1.00	
4 - 2	−0.01	0.02	−0.48	0.99	
5 - 2	−0.11	0.02	−5.54	<0.001	***
4 - 3	−0.01	0.02	−0.32	1.00	
5 - 3	−0.11	0.02	−5.30	<0.001	***
5 - 4	−0.10	0.02	−4.92	<0.001	***

Table A.6: Experiment III, Same-Different Task, *Different* trials, Reaction Times: Post-hoc Comparisons across Positions.

References

Abla, D., Katahira, K., & Okanoya, K. (2008). On-line assessment of statistical learning by event-related potentials. *Journal of Cognitive Neuroscience*, *20*(6), 952–964.

Adelman, J. S., Marquis, S. J., & Sabatos-DeVito, M. G. (2010). Letters in words are read simultaneously, not in left-to-right sequence. *Psychological Science*, *21*(12), 1799–1801.

Adler, F. H., & Fliegelman, M. (1934). Influence of fixation on the visual acuity. *Archives of Ophthalmology*, *12*(4), 475–483.

Aghababian, V., & Nazir, T. A. (2000). Developing normal reading skills: Aspects of the visual processes underlying word recognition. *Journal of experimental child psychology*, *76*(2), 123–150.

Algeo, J., & Algeo, A. S. (1993). *Fifty years among the new words: A dictionary of neologisms 1941-1991*. Cambridge University Press.

Alhama, R. G., Siegelman, N., Frost, R., & Armstrong, B. C. (2019). The role of information in visual word recognition: A perceptually-constrained connectionist account. *The 41st annual meeting of the cognitive science society (cogsci 2019)*, 83–89.

Alonso-Prieto, E., Van Belle, G., Liu-Shuang, J., Norcia, A. M., & Rossion, B. (2013). The 6 hz fundamental stimulation frequency rate for individual face discrimination in the right occipito-temporal cortex. *Neuropsychologia*, *51*(13), 2863–2875.

Amado, C., & Kovács, G. (2016). Does surprise enhancement or repetition suppression explain visual mismatch negativity? *European Journal of Neuroscience*, *43*(12), 1590–1600.

Amenta, S., & Crepaldi, D. (2012). Morphological processing as we know it: An analytical review of morphological effects in visual word identification. *Frontiers in psychology*, *3*, 232.

Amenta, S., Günther, F., & Marelli, M. (2020). A (distributional) semantic perspective on the processing of morphologically complex words. *The Mental Lexicon*, *15*(1), 62–78.

Andrews, S. (1992). Frequency and neighborhood effects on lexical access: Lexical similarity or orthographic redundancy? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *18*(2), 234.

Angiolillo-Bent, J. S., & Rips, L. J. (1982). Order information in multiple-element comparison. *Journal of Experimental Psychology: Human Perception and Performance*, *8*(3), 392.

Aparicio, M., Gounot, D., Demont, E., & Metz-Lutz, M.-N. (2007). Phonological processing in relation to reading: An fmri study in deaf readers. *Neuroimage*, *35*(3), 1303–1316.

Araújo, S., Faısca, L., Bramão, I., Reis, A., & Petersson, K. M. (2015). Lexical and sublexical orthographic processing: An erp study with skilled and dyslexic adult readers. *Brain and Language*, *141*, 16–27.

Arciuli, J., & Simpson, I. C. (2012). Statistical learning is related to reading ability in children and adults. *Cognitive science*, *36*(2), 286–304.

Arciuli, J., & Torkildsen, J. V. K. (2012). Advancing our understanding of the link between statistical learning and language acquisition: The need for longitudinal data. *Frontiers in psychology*, *3*, 324.

Armstrong, B. C., Frost, R., & Christiansen, M. H. (2017). The long road of statistical learning research: Past, present and future.

Asanowicz, D., Verleger, R., Kruse, L., Beier, K., & Śmigasiewicz, K. (2017). A right hemisphere advantage at early cortical stages of processing alphanumeric stimuli. evidence from electrophysiology. *Brain and cognition*, *113*, 40–55.

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.

Aslin, R. N. (2017). Statistical learning: A powerful mechanism that operates by mere exposure. *Wiley Interdisciplinary Reviews: Cognitive Science*, *8*(1-2), e1373.

Aslin, R. N., Saffran, J. R., & Newport, E. L. (1998). Computation of conditional probability statistics by 8-month-old infants. *Psychological science*, *9*(4), 321–324.

Avarguès-Weber, A., Finke, V., Nagy, M., Szabó, T., d'Amaro, D., Dyer, A. G., & Fiser, J. (2020). Different mechanisms underlie implicit visual statistical learning in honey bees and humans. *Proceedings of the National Academy of Sciences*, *117*(41), 25923–25934.

Averbach, E., & Coriell, A. S. (1961). Short-term memory in vision. *The Bell System Technical Journal*, *40*(1), 309–328.

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.

Baayen, R. H., Dijkstra, T., & Schreuder, R. (1997). Singulars and plurals in dutch: Evidence for a parallel dual-route model. *Journal of Memory and Language*, *37*(1), 94–117.

Baayen, R. H., Milin, P., Đurđević, 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.

Baayen, R. H., Milin, P., & Ramscar, M. (2016). Frequency in lexical processing. *Aphasiology*, *30*(11), 1174–1220.

Baayen, R. H., Wurm, L. H., & Aycock, J. (2007). Lexical dynamics for low-frequency complex words: A regression study across tasks and modalities. *The mental lexicon*, *2*(3), 419–463.

Baker, C. I., Behrmann, M., & Olson, C. R. (2002). Impact of learning on representation of parts and wholes in monkey inferotemporal cortex. *Nature neuroscience*, *5*(11), 1210–1216.

Balas, B., Nakano, L., & Rosenholtz, R. (2009). A summary-statistic representation in peripheral vision explains visual crowding. *Journal of vision*, *9*(12), 13–13.

Balota, D. A., Yap, M. J., Hutchison, K. A., Cortese, M. J., 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.

Barber, H. A., & Kutas, M. (2007). Interplay between computational models and cognitive electrophysiology in visual word recognition. *Brain research reviews*, *53*(1), 98–123.

Baron, J., & Thurston, I. (1973). An analysis of the word-superiority effect. *Cognitive psychology*, *4*(2), 207–228.

Barron, R. W., & Pittenger, J. B. (1974). The effect of orthographic structure and lexical meaning on "same-different" judgments. *Quarterly Journal of Experimental Psychology*, *26*(4), 566–581.

Bates, D., Sarkar, D., Bates, M. D., & Matrix, L. (2007). The lme4 package. *R package version*, *2*(1), 74.

Bellocchi, S. (2013). Developmental dyslexia, visual crowding and eye movements. *Eye movement: Developmental perspectives, dysfunctions and disorders in humans*, 93–110.

Beyersmann, E., Casalis, S., Ziegler, J. C., & Grainger, J. (2015). Language proficiency and morpho-orthographic segmentation. *Psychonomic bulletin & review*, *22*(4), 1054–1061.

Beyersmann, E., Cavalli, E., Casalis, S., & Colé, P. (2016). Embedded stem priming effects in prefixed and suffixed pseudowords. *Scientific Studies of Reading*, *20*(3), 220–230.

Beyersmann, E., & Grainger, J. (2018). Support from the morphological family when unembedding the stem. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *44*(1), 135.

Beyersmann, E., Kezilas, Y., Coltheart, M., Castles, A., Ziegler, J. C., Taft, M., & Grainger, J. (2018). Taking the book from the bookshelf: Masked constituent priming effects from compound words and nonwords. *Journal of cognition*, *1*(1).

Beyersmann, E., Montani, V., Ziegler, J. C., Grainger, J., & Stoianov, I. P. (2021). The dynamics of reading complex words: Evidence from steady-state visual evoked potentials. *Scientific Reports*, *11*(1), 1–14.

Beyersmann, E., Mousikou, P., Javourey-Drevet, L., Schroeder, S., Ziegler, J. C., & Grainger, J. (2020). Morphological processing across modalities and languages. *Scientific Studies of Reading*, *24*(6), 500–519.

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.

Beyersmann, E., Ziegler, J. C., & Grainger, J. (2015). Differences in the processing of prefixes and suffixes revealed by a letter-search task. *Scientific Studies of Reading*, *19*(5), 360–373.

Biederman, G. B. (1966). Supplementary report: The recognition of tachistoscopically presented five-letter words as a function of digram frequency. *Journal of Verbal Learning and Verbal Behavior*, *5*(2), 208–209.

Biederman, I. (1987). Recognition-by-components: A theory of human image understanding. *Psychological review*, *94*(2), 115.

Binder, J., & Price, C. J. (2001). Functional neuroimaging of language. *Handbook of functional neuroimaging of cognition*, 187–251.

Binder, J. R., Medler, D. A., Westbury, C. F., Liebenthal, E., & Buchanan, L. (2006). Tuning of the human left fusiform gyrus to sublexical orthographic structure. *Neuroimage*, *33*(2), 739–748.

Bloomfield, L. (1933). Language. New York, NY: Henry Holt.

Bogaerts, L., Frost, R., & Christiansen, M. H. (2020). Integrating statistical learning into cognitive science. *Journal of Memory and Language*, *115*, 104167.

Bogaerts, L., Siegelman, N., & Frost, R. (2016). Splitting the variance of statistical learning performance: A parametric investigation of exposure duration and transitional probabilities. *Psychonomic bulletin & review*, *23*(4), 1250–1256.

Booth, M., & Rolls, E. T. (1998). View-invariant representations of familiar objects by neurons in the inferior temporal visual cortex. *Cerebral cortex (New York, NY: 1991)*, *8*(6), 510–523.

Borowsky, R., Esopenko, C., Cummine, J., & Sarty, G. E. (2007). Neural representations of visual words and objects: A functional mri study on the modularity of reading and object processing. *Brain topography*, *20*(2), 89–96.

Bouma, H. (1970). Interaction effects in parafoveal letter recognition. *Nature*, *226*(5241), 177–178.

Bouma, H. (1973). Visual interference in the parafoveal recognition of initial and final letters of words. *Vision research*, *13*(4), 767–782.

Bowers, J. S. (2009). On the biological plausibility of grandmother cells: Implications for neural network theories in psychology and neuroscience. *Psychological review*, *116*(1), 220.

Bowers, J. S. (2017). Parallel distributed processing theory in the age of deep networks. *Trends in cognitive sciences*, *21*(12), 950–961.

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial vision*, *10*(4), 433–436.

Braun, M., Hutzler, F., Münte, T. F., Rotte, M., Dambacher, M., Richlan, F., & Jacobs, A. M. (2015). The neural bases of the pseudohomophone effect: Phonological constraints on lexico-semantic access in reading. *Neuroscience*, *295*, 151–163.

Bricolo, E., Salvi, C., Martelli, M., Arduino, L. S., & Daini, R. (2015). The effects of crowding on eye movement patterns in reading. *Acta psychologica*, *160*, 23–34.

Brysbaert, M., Mandera, P., & Keuleers, E. (2018). The word frequency effect in word processing: An updated review. *Current Directions in Psychological Science*, *27*(1), 45–50.

Brysbaert, M., & New, B. (2009). Moving beyond kučera 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.

Bullmore, E. T., Suckling, J., Overmeyer, S., Rabe-Hesketh, S., Taylor, E., & Brammer, M. J. (1999). Global, voxel, and cluster tests, by theory and permutation, for a difference between two groups of structural mr images of the brain. *IEEE transactions on medical imaging*, *18*(1), 32–42.

Burani, C., Arduino, L. S., & Marcolini, S. (2006). Naming morphologically complex pseudowords: A headstart for the root? *The Mental Lexicon*, *1*(2), 299–327.

Burani, C., Salmaso, D., & Caramazza, A. (1984). Morphological structure and lexical access. *Visible Language*, *18*(4), 342–352.

Burani, C., & Thornton, A. M. (2003). The interplay of root, suffix and whole-word frequency in processing derived words. *Trends in Linguistics Studies and Monographs*, *151*, 157–208.

Bybee, J. L. (1988). Morphology as lexical organization. *Theoretical morphology, 119141.*

Carr, T. H. (1986). Perceiving visual language. *Handbook of perception and human performance* (29:1–29:92). John Wiley & Sons.

Carr, T. H. (1999). Trying to understand reading and dyslexia: Mental chronometry, individual differences, cognitive neuroscience, and the impact of instruction as converging sources of evidence. *Converging methods for understanding reading and dyslexia*, 459–491.

Carr, T. H., Posner, M. I., Pollatsek, A., & Snyder, C. R. (1979). Orthography and familiarity effects in word processing. *Journal of Experimental Psychology: General*, *108*(4), 389.

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.

Carreiras, M., & Perea, M. (2002). Masked priming effects with syllabic neighbors in a lexical decision task. *Journal of Experimental Psychology: human perception and performance*, *28*(5), 1228.

Carreiras, M., & Price, C. J. (2008). Brain activation for consonants and vowels. *Cerebral Cortex*, *18*(7), 1727–1735.

Carreiras, M., Vergara, M., & Perea, M. (2009). Erp correlates of transposed-letter priming effects: The role of vowels versus consonants. *Psychophysiology*, *46*(1), 34–42.

Cassar, M., & Treiman, R. (1997). The beginnings of orthographic knowledge: Children's knowledge of double letters in words. *Journal of educational psychology*, *89*(4), 631.

Castet, E., Descamps, M., Denis-Noël, A., & Cole, P. (2017). Letter and symbol identification: No evidence for letter-specific crowding mechanisms. *Journal of vision*, *17*(11), 2–2.

Castles, A., Rastle, K., & Nation, K. (2018). Ending the reading wars: Reading acquisition from novice to expert. *Psychological Science in the Public Interest*, *19*(1), 5–51.

Cattell, J. M. (1886). The time it takes to see and name objects. *Mind*, *11*(41), 63–65.

Chanceaux, M., & Grainger, J. (2012). Serial position effects in the identification of letters, digits, symbols, and shapes in peripheral vision. *Acta psychologica*, *141*(2), 149–158.

Chanceaux, M., Mathôt, S., & Grainger, J. (2013). Flank to the left, flank to the right: Testing the modified receptive field hypothesis of letter-specific crowding. *Journal of Cognitive Psychology*, *25*(6), 774–780.

Changizi, M. A., Zhang, Q., Ye, H., & Shimojo, S. (2006). The structures of letters and symbols throughout human history are selected to match those found in objects in natural scenes. *The American Naturalist*, *167*(5), E117–E139.

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.

Chetail, F. (2015). Reconsidering the role of orthographic redundancy in visual word recognition. *Frontiers in Psychology*, *6*, 645.

Chetail, F. (2017). What do we do with what we learn? Statistical learning of orthographic regularities impacts written word processing. *Cognition*, *163*, 103–120.

Chetail, F., & Boursain, E. (2019). Shared or separated representations for letters with diacritics? *Psychonomic bulletin & review*, *26*(1), 347–352.

Chomsky, N. (1980). Rules and representations. *Behavioral and brain sciences*, *3*(1), 1–15.

Chomsky, N. (2011). Language and other cognitive systems. what is special about language? *Language learning and development*, *7*(4), 263–278.

Christiansen, M. H. (2019). Implicit statistical learning: A tale of two literatures. *Topics in Cognitive Science*, *11*(3), 468–481.

Clark, J. J., & O'regan, J. K. (1999). Word ambiguity and the optimal viewing position in reading. *Vision Research*, *39*(4), 843–857.

Cohen, L., Dehaene, S., Vinckier, F., Jobert, A., & Montavont, A. (2008). Reading normal and degraded words: Contribution of the dorsal and ventral visual pathways. *Neuroimage*, *40*(1), 353–366.

Cohen, L., Lehéricy, S., Chochon, F., Lemer, C., Rivaud, S., & Dehaene, S. (2002). Language-specific tuning of visual cortex? functional properties of the visual word form area. *Brain*, *125*(5), 1054–1069.

Colé, P., Beauvillain, C., & Segui, J. (1989). On the representation and processing of prefixed and suffixed derived words: A differential frequency effect. *Journal of Memory and language*, *28*(1), 1–13.

Coll, M.-P., Murphy, J., Catmur, C., Bird, G., & Brewer, R. (2019). The importance of stimulus variability when studying face processing using fast periodic visual stimulation: A novel 'mixed-emotions' paradigm. *Cortex*, *117*, 182–195.

Coltheart, M. (1978). Lexical access in simple reading tasks. *Strategies of information processing*, 151–216.

Coltheart, M. (2006). Dual route and connectionist models of reading: An overview. *London Review of Education*, *4*(1), 5–17.

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.

Conrad, N. J., Harris, N., & Williams, J. (2013). Individual differences in children's literacy development: The contribution of orthographic knowledge. *Reading and Writing*, *26*(8), 1223–1239.

Conway, C. M., & Christiansen, M. H. (2005). Modality-constrained statistical learning of tactile, visual, and auditory sequences. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *31*(1), 24.

Crepaldi, D., Keuleers, E., Mandera, P., & Brysbaert, M. (2013). Subtlex-it.

Crepaldi, D., Rastle, K., & Davis, C. J. (2010). Morphemes in their place: Evidence for position-specific identification of suffixes. *Memory & cognition*, *38*(3), 312–321.

Dale, A. M., Liu, A. K., Fischl, B. R., Buckner, R. L., Belliveau, J. W., Lewine, J. D., & Halgren, E. (2000). Dynamic statistical parametric mapping: Combining fmri and meg for high-resolution imaging of cortical activity. *neuron*, *26*(1), 55–67.

Davis, M. H., Meunier, F., & Marslen-Wilson, W. D. (2004). Neural responses to morphological, syntactic, and semantic properties of single words: An fmri study. *Brain and language*, *89*(3), 439–449.

Davis, M. H., & Rastle, K. (2010). Form and meaning in early morphological processing: Comment on feldman, o'connor, and moscoso del prado martın (2009). *Psychonomic bulletin & review*, *17*(5), 749–755.

Dehaene, S., & Cohen, L. (2007). Cultural recycling of cortical maps. *Neuron*, *56*(2), 384–398.

Dehaene, S., & Cohen, L. (2011). The unique role of the visual word form area in reading. *Trends in cognitive sciences*, *15*(6), 254–262.

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.

Dehaene, S., Cohen, L., Sigman, M., & Vinckier, F. (2005). The neural code for written words: A proposal. *Trends in cognitive sciences*, *9*(7), 335–341.

Dehaene, S., Jobert, A., Naccache, L., Ciuciu, P., Poline, J.-B., Le Bihan, D., & Cohen, L. (2004). Letter binding and invariant recognition of masked words: Behavioral and neuroimaging evidence. *Psychological science*, *15*(5), 307–313.

Dehaene, S., Le Clec'H, G., Poline, J.-B., Le Bihan, D., & Cohen, L. (2002). The visual word form area: A prelexical representation of visual words in the fusiform gyrus. *Neuroreport*, *13*(3), 321–325.

Dehaene, S., Naccache, L., Cohen, L., Le Bihan, D., Mangin, J.-F., Poline, J.-B., & Rivière, D. (2001). Cerebral mechanisms of word masking and unconscious repetition priming. *Nature neuroscience*, *4*(7), 752–758.

Dejerine, J. (1892). Contribution à l'étude anatomopathologique et clinique des différents variétés de cécité verbale. *Mémoires de la Société de Biologie*, *4*, 61–90.

Delorme, A., & Makeig, S. (2004). Eeglab: An open source toolbox for analysis of single-trial eeg dynamics including independent component analysis. *Journal of neuroscience methods*, *134*(1), 9–21.

Desikan, R. S., Ségonne, F., Fischl, B., Quinn, B. T., Dickerson, B. C., Blacker, D., Buckner, R. L., Dale, A. M., Maguire, R. P., Hyman, B. T., et al. (2006). An automated labeling system for subdividing the human cerebral cortex on mri scans into gyral based regions of interest. *Neuroimage*, *31*(3), 968–980.

Devereux, B. J., Clarke, A., Marouchos, A., & Tyler, L. K. (2013). Representational similarity analysis reveals commonalities and differences in the semantic processing of words and objects. *Journal of Neuroscience*, *33*(48), 18906–18916.

Devlin, J. T., Jamison, H. L., Matthews, P. M., & Gonnerman, L. M. (2004). Morphology and the internal structure of words. *Proceedings of the National Academy of Sciences*, *101*(41), 14984–14988.

DiCarlo, J. J., Zoccolan, D., & Rust, N. C. (2012). How does the brain solve visual object recognition? *Neuron*, *73*(3), 415–434.

Dien, J., Brian, E. S., Molfese, D. L., & Gold, B. T. (2013). Combined erp/fmri evidence for early word recognition effects in the posterior inferior temporal gyrus. *Cortex*, *49*(9), 2307–2321.

Dienes, Z. (2014). Using bayes to get the most out of non-significant results. *Frontiers in psychology*, *5*, 781.

Dietz, N. A., Jones, K. M., Gareau, L., Zeffiro, T. A., & Eden, G. F. (2005). Phonological decoding involves left posterior fusiform gyrus. *Human brain mapping*, *26*(2), 81–93.

Ducrot, S., Pynte, J., Ghio, A., & Lété, B. (2013). Visual and linguistic determinants of the eyes' initial fixation position in reading development. *Acta psychologica*, *142*(3), 287–298.

Duñabeitia, J. A., Kinoshita, S., Carreiras, M., & Norris, D. (2011). Is morpho-orthographic decomposition purely orthographic? evidence from masked priming in the same–different task. *Language and Cognitive Processes*, *26*(4-6), 509–529.

D'ydewalle, G., & Auwers, T. (1994). Orthographic redundancy in letter recognition: Orthographic neighbourhood or orthographic context? *European Journal of Cognitive Psychology*, *6*(3), 287–310.

Dzhelyova, M., & Rossion, B. (2014). Supra-additive contribution of shape and surface information to individual face discrimination as revealed by fast periodic visual stimulation. *Journal of Vision*, *14*(14), 15–15.

Ellis, N. C. (2002). Reflections on frequency effects in language processing. *Studies in second language acquisition*, 297–339.

Endress, A. D., & Mehler, J. (2009). The surprising power of statistical learning: When fragment knowledge leads to false memories of unheard words. *Journal of Memory and Language*, *60*(3), 351–367.

Fahle, M., Poggio, T., Poggio, T. A., et al. (2002). *Perceptual learning.* MIT Press.

Feldman, L. B., & Basnight-Brown, D. M. (2008). The role of morphology in visual word recognition: Graded semantic influences due to competing senses and semantic richness of the stem. *Single-word reading: Behavioral and biological perspectives*, 85–106.

Feldman, L. B., Kostić, A., Gvozdenović, V., O'Connor, P. A., & del Prado Martın, F. M. (2012). Semantic similarity influences early morphological priming in serbian: A challenge to form-then-meaning accounts of word recognition. *Psychonomic bulletin & review*, *19*(4), 668–676.

Feldman, L. B., O'Connor, P. A., & del Prado Martın, F. M. (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.

Feuerriegel, D., Keage, H. A., Rossion, B., & Quek, G. L. (2018). Immediate stimulus repetition abolishes stimulus expectation and surprise effects in fast periodic visual oddball designs. *Biological psychology*, *138*, 110–125.

Fiebach, C. J., Friederici, A. D., Müller, K., & Von Cramon, D. Y. (2002). Fmri evidence for dual routes to the mental lexicon in visual word recognition. *Journal of cognitive neuroscience*, *14*(1), 11–23.

Fiez, J. A., Balota, D. A., Raichle, M. E., & Petersen, S. E. (1999). Effects of lexicality, frequency, and spelling-to-sound consistency on the functional anatomy of reading. *Neuron*, *24*(1), 205–218.

Fiez, J. A., & Petersen, S. E. (1998). Neuroimaging studies of word reading. *Proceedings of the National Academy of Sciences*, *95*(3), 914–921.

Finley, S., & Newport, E. (2021). Non-concatenative morpheme segmentation in adults and children.

Fischer-Baum, S., Charny, J., & McCloskey, M. (2011). Both-edges representation of letter position in reading. *Psychonomic Bulletin & Review*, *18*(6), 1083–1089.

Fischl, B. (2012). Freesurfer. *Neuroimage*, *62*(2), 774–781.

Fiser, J., & Aslin, R. N. (2001). Unsupervised statistical learning of higher-order spatial structures from visual scenes. *Psychological science*, *12*(6), 499–504.

Fiser, J., & Aslin, R. N. (2002). Statistical learning of higher-order temporal structure from visual shape sequences. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *28*(3), 458.

Fiser, J., & Aslin, R. N. (2005). Encoding multielement scenes: Statistical learning of visual feature hierarchies. *Journal of Experimental Psychology: General*, *134*(4), 521.

Flom, M. C., Heath, G. G., & Takahashi, E. (1963). Contour interaction and visual resolution: Contralateral effects. *Science*, *142*(3594), 979–980.

Forster, K. I. (1998). The pros and cons of masked priming. *Journal of psycholinguistic research*, *27*(2), 203–233.

Forster, K. I., & Davis, C. (1984). Repetition priming and frequency attenuation in lexical access. *Journal of experimental psychology: Learning, Memory, and Cognition*, *10*(4), 680.

Francis, G., Manassi, M., & Herzog, M. H. (2017). Neural dynamics of grouping and segmentation explain properties of visual crowding. *Psychological review*, *124*(4), 483.

Franco, A., Eberlen, J., Destrebecqz, A., Cleeremans, A., & Bertels, J. (2015). Rapid serial auditory presentation. *Experimental psychology*.

Franzen, L., Stark, Z., & Johnson, A. P. (2021). Individuals with dyslexia use a different visual sampling strategy to read text. *Scientific reports*, *11*(1), 1–17.

Friston, K. (2005). A theory of cortical responses. *Philosophical transactions of the Royal Society B: Biological sciences*, *360*(1456), 815–836.

Frost, R. (2012). Towards a universal model of reading. *The Behavioral and brain sciences*, *35*(5), 263.

Frost, R., Armstrong, B. C., & Christiansen, M. H. (2019). Statistical learning research: A critical review and possible new directions. *Psychological Bulletin*, *145*(12), 1128.

Frost, R., Armstrong, B. C., Siegelman, N., & Christiansen, M. H. (2015). Domain generality versus modality specificity: The paradox of statistical learning. *Trends in cognitive sciences*, *19*(3), 117–125.

Frost, R., Siegelman, N., Narkiss, A., & Afek, L. (2013). What predicts successful literacy acquisition in a second language? *Psychological science*, *24*(7), 1243–1252.

Frost, S. J., Mencl, W. E., Sandak, R., Moore, D. L., Rueckl, J. G., Katz, L., Fulbright, R. K., & Pugh, K. R. (2005). A functional magnetic resonance imaging study of the tradeoff between semantics and phonology in reading aloud. *Neuroreport*, *16*(6), 621–624.

Gallistel, C. R. (2011). Prelinguistic thought. *Language learning and development*, *7*(4), 253–262.

Garrido, M. I., Kilner, J. M., Stephan, K. E., & Friston, K. J. (2009). The mismatch negativity: A review of underlying mechanisms. *Clinical neurophysiology*, *120*(3), 453–463.

Gibson, E. J. (1971). Perceptual learning and the theory of word perception. *Cognitive Psychology*, *2*(4), 351–368.

Gilbert, C. D., Sigman, M., & Crist, R. E. (2001). The neural basis of perceptual learning. *Neuron*, *31*(5), 681–697.

Giraudo, H., Dal Maso, S., & Piccinin, S. (2016). The role of stem frequency in morphological processing. *Mediterranean morphology meetings*, *10*, 64–72.

Giraudo, H., & Voga, M. (2014). Measuring morphology: The tip of the iceberg? a retrospective on 10 years of morphological processing.

Giraudo, H., & Voga, M. (2016). Words matter more than morphemes: An investigation of masked priming effects with complex words and nonwords. *Italian Journal of Linguistics/Rivista di linguistica*, *28*, 49–78.

Glezer, L. S., Jiang, X., & Riesenhuber, M. (2009). Evidence for highly selective neuronal tuning to whole words in the "visual word form area". *Neuron*, *62*(2), 199–204.

Gold, B. T., & Rastle, K. (2007). Neural correlates of morphological decomposition during visual word recognition. *Journal of Cognitive Neuroscience*, *19*(12), 1983–1993.

Goldstone, R. L. (1998). Perceptual learning. *Annual review of psychology*, *49*(1), 585–612.

Goodman, K. S. (1971). Decoding-from code to what? *Journal of reading*, *14*(7), 455–498.

Gori, S., & Facoetti, A. (2015). How the visual aspects can be crucial in reading acquisition: The intriguing case of crowding and developmental dyslexia. *Journal of vision*, *15*(1), 8–8.

Grainger, J. (2008). Cracking the orthographic code: An introduction. *Language and cognitive processes*, *23*(1), 1–35.

Grainger, J. (2018). Orthographic processing: A 'mid-level'vision of reading: The 44th sir frederic bartlett lecture. *Quarterly Journal of Experimental Psychology*, *71*(2), 335–359.

Grainger, J., Bertrand, D., Lété, B., Beyersmann, E., & Ziegler, J. C. (2016). A developmental investigation of the first-letter advantage. *Journal of Experimental Child Psychology*, *152*, 161–172.

Grainger, J., & Beyersmann, E. (2017). Edge-aligned embedded word activation initiates morpho-orthographic segmentation. *Psychology of learning and motivation* (pp. 285–317). Elsevier.

Grainger, J., & Beyersmann, E. (2020). Effects of lexicality and pseudo-morphological complexity on embedded word priming. *Journal of Experimental Psychology: Learning, Memory, and Cognition.*

Grainger, J., Dufau, S. et al. (2012). The front-end of visual word recognition. *Visual word recognition*, *1*, 159–184.

Grainger, J., Dufau, S., Montant, M., Ziegler, J. C., & Fagot, J. (2012). Orthographic processing in baboons (papio papio). *Science*, *336*(6078), 245–248.

Grainger, J., Dufau, S., & Ziegler, J. C. (2016). A vision of reading. *Trends in Cognitive Sciences*, *20*(3), 171–179.

Grainger, J., & Hannagan, T. (2014). What is special about orthographic processing? *Written Language & Literacy*, *17*(2), 225–252.

Grainger, J., & Jacobs, A. M. (1994). A dual read-out model of word context effects in letter perception: Further investigations of the word superiority effect. *Journal of Experimental Psychology: Human Perception and Performance*, *20*(6), 1158.

Grainger, J., & Jacobs, A. M. (1996). Orthographic processing in visual word recognition: A multiple read-out model. *Psychological review*, *103*(3), 518.

Grainger, J., & Ziegler, J. (2011). A dual-route approach to orthographic processing. *Frontiers in psychology*, *2*, 54.

Greenwood, J. A., Bex, P. J., & Dakin, S. C. (2009). Positional averaging explains crowding with letter-like stimuli. *Proceedings of the National Academy of Sciences*, *106*(31), 13130–13135.

Grill-Spector, K., Henson, R., & Martin, A. (2006). Repetition and the brain: Neural models of stimulus-specific effects. *Trends in cognitive sciences*, *10*(1), 14–23.

Gu, J., & Li, X. (2015). The effects of character transposition within and across words in chinese reading. *Attention, Perception, & Psychophysics*, *77*(1), 272–281.

Günther, F., & Marelli, M. (2020). Trying to make it work: Compositional effects in the processing of compound “nonwords”. *Quarterly Journal of Experimental Psychology*, *73*(7), 1082–1091.

Haber, R. N., & Standing, L. (1969). Location of errors with a post-stimulus indicator. *Psychonomic Science*, *17*(6), 345–346.

Hämäläinen, M. S., & Ilmoniemi, R. J. (1994). Interpreting magnetic fields of the brain: Minimum norm estimates. *Medical & biological engineering & computing*, *32*(1), 35–42.

Harrison, W. J., & Bex, P. J. (2017). Visual crowding is a combination of an increase of positional uncertainty, source confusion, and featural averaging. *Scientific reports*, *7*(1), 1–9.

Hasenäcker, J., Beyersmann, E., & Schroeder, S. (2016). Masked morphological priming in german-speaking adults and children: Evidence from response time distributions. *Frontiers in Psychology*, *7*, 929.

Hasenäcker, J., Beyersmann, E., & Schroeder, S. (2020). Morphological priming in children: Disentangling the effects of school-grade and reading skill. *Scientific Studies of Reading*, 1–16.

Hasenäcker, J., Ktori, M., & Crepaldi, D. (2021). Morpheme position coding in reading development as explored with a letter search task. *Journal of cognition*, *4*(1).

Heathcote, L., Nation, K., Castles, A., & Beyersmann, E. (2018). Do 'blacheap' and 'subcheap' both prime 'cheap'? An investigation of morphemic status and position in early visual word processing. *Quarterly Journal of Experimental Psychology*, *71*(8), 1645–1654.

Heilbron, M., Richter, D., Ekman, M., Hagoort, P., & De Lange, F. P. (2020). Word contexts enhance the neural representation of individual letters in early visual cortex. *Nature communications*, *11*(1), 1–11.

Hellige, J. B., & Michimata, C. (1989). Visual laterality for letter comparison: Effects of stimulus factors, response factors, and metacontrol. *Bulletin of the Psychonomic Society*, *27*(5), 441–444.

Henson, R., Rylands, A., Ross, E., Vuilleumeir, P., & Rugg, M. D. (2004). The effect of repetition lag on electrophysiological and haemodynamic correlates of visual object priming. *Neuroimage*, *21*(4), 1674–1689.

Herzog, M. H., Sayim, B., Chicherov, V., & Manassi, M. (2015). Crowding, grouping, and object recognition: A matter of appearance. *Journal of vision*, *15*(6), 5–5.

Hothorn, T., Bretz, F., Westfall, P., Heiberger, R. M., Schuetzenmeister, A., Scheibe, S., & Hothorn, M. T. (2016). Package 'multcomp'. *Simultaneous inference in general parametric models. Project for Statistical Computing, Vienna, Austria.*

Hsu, H. J., Tomblin, J. B., & Christiansen, M. H. (2014). Impaired statistical learning of non-adjacent dependencies in adolescents with specific language impairment. *Frontiers in psychology*, *5*, 175.

Huang, M., Mosher, J. C., & Leahy, R. (1999). A sensor-weighted overlapping-sphere head model and exhaustive head model comparison for meg. *Physics in Medicine & Biology*, *44*(2), 423.

Huckauf, A., & Nazir, T. A. (2007). How odgcrnwi becomes crowding: Stimulus-specific learning reduces crowding. *Journal of Vision*, *7*(2), 18–18.

Huey, E. B. (1908). The psychology and pedagogy of reading: With a review of the history of reading and writing and of methods, texts, and hygiene in reading.

Hunt, R. H., & Aslin, R. N. (2001). Statistical learning in a serial reaction time task: Access to separable statistical cues by individual learners. *Journal of Experimental Psychology: General*, *130*(4), 658.

Hyönä, J., Niemi, P., & Underwood, G. (1989). Reading long words embedded in sentences: Informativeness of word halves affects eye movements. *Journal of Experimental Psychology: Human Perception and Performance*, *15*(1), 142.

Ischebeck, A., Indefrey, P., Usui, N., Nose, I., Hellwig, F., & Taira, M. (2004). Reading in a regular orthography: An fmri study investigating the role of visual familiarity. *Journal of Cognitive Neuroscience*, *16*(5), 727–741.

Jacobs, A. M., & Grainger, J. (1992). Testing a semistochastic variant of the interactive activation model in different word recognition experiments. *Journal of Experimental Psychology: Human perception and performance*, *18*(4), 1174.

Jacobs, A. M., Rey, A., Ziegler, J. C., & Grainger, J. (2013). Mrom-p: An interactive activation, multiple readout model of orthographic and phonological processes in visual word recognition. *Localist connectionist approaches to human cognition* (pp. 157–198). Psychology Press.

Jacques, C., Retter, T. L., & Rossion, B. (2016). A single glance at natural face images generate larger and qualitatively different category-selective spatio-temporal signatures than other ecologically-relevant categories in the human brain. *NeuroImage*, *137*, 21–33.

Jeon, S. T., Hamid, J., Maurer, D., & Lewis, T. L. (2010). Developmental changes during childhood in single-letter acuity and its crowding by surrounding contours. *Journal of experimental child psychology*, *107*(4), 423–437.

Johnson, R. L., Perea, M., & Rayner, K. (2007). Transposed-letter effects in reading: Evidence from eye movements and parafoveal preview. *Journal of Experimental Psychology: Human Perception and Performance*, *33*(1), 209.

Jonsson, J. E., & Hellige, J. B. (1986). Lateralized effects of blurring: A test of the visual spatial frequency model of cerebral hemisphere asymmetry. *Neuropsychologia*, *24*(3), 351–362.

Jutten, C., & Herault, J. (1991). Blind separation of sources, part i: An adaptive algorithm based on neuromimetic architecture. *Signal processing*, *24*(1), 1–10.

Karpicke, J. D., & Pisoni, D. B. (2004). Using immediate memory span. *Memory & cognition*, *32*(6), 956–964.

Keller, T. A., Carpenter, P. A., & Just, M. A. (2001). The neural bases of sentence comprehension: A fmri examination of syntactic and lexical processing. *Cerebral cortex*, *11*(3), 223–237.

Kennedy, A., Heller, D., Pynte, J., & Radach, R. (2000). Traces of print along the visual pathway. *Reading as a perceptual process* (pp. 39–56). Elsevier.

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.

Kimura, M., Schröger, E., & Czigler, I. (2011). Visual mismatch negativity and its importance in visual cognitive sciences. *Neuroreport*, *22*(14), 669–673.

Kinoshita, S., & Lupker, S. J. (2004). *Masked priming: The state of the art.* Psychology Press.

Kinoshita, S., & Norris, D. (2009). Transposed-letter priming of prelexical orthographic representations. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *35*(1), 1.

Kinoshita, S., Yu, L., Verdonschot, R. G., & Norris, D. (2021). Letter identity and visual similarity in the processing of diacritic letters. *Memory & Cognition*, *49*(4), 815–825.

Kirkham, N. Z., Slemmer, J. A., & Johnson, S. P. (2002). Visual statistical learning in infancy: Evidence for a domain general learning mechanism. *Cognition*, *83*(2), B35–B42.

Kóbor, A., Janacsek, K., Takács, Á., & Nemeth, D. (2017). Statistical learning leads to persistent memory: Evidence for one-year consolidation. *Scientific reports*, *7*(1), 1–10.

Koelsch, S., Busch, T., Jentschke, S., & Rohrmeier, M. (2016). Under the hood of statistical learning: A statistical mmn reflects the magnitude of transitional probabilities in auditory sequences. *Scientific reports*, *6*(1), 1–11.

Kohn, A. (2007). Visual adaptation: Physiology, mechanisms, and functional benefits. *Journal of neurophysiology*, *97*(5), 3155–3164.

Kronbichler, M., Bergmann, J., Hutzler, F., Staffen, W., Mair, A., Ladurner, G., & Wimmer, H. (2007). Taxi vs. taksi: On orthographic word recognition in the left ventral occipitotemporal cortex. *Journal of cognitive neuroscience*, *19*(10), 1584–1594.

Kronbichler, M., Hutzler, F., Wimmer, H., Mair, A., Staffen, W., & Ladurner, G. (2004). The visual word form area and the frequency with which words are encountered: Evidence from a parametric fmri study. *Neuroimage*, *21*(3), 946–953.

Kronbichler, M., Klackl, J., Richlan, F., Schurz, M., Staffen, W., Ladurner, G., & Wimmer, H. (2009). On the functional neuroanatomy of visual word processing: Effects of case and letter deviance. *Journal of Cognitive Neuroscience*, *21*(2), 222–229.

Krueger, L. E. (1975). The word-superiority effect: Is its locus visual-spatial or verbal? *Bulletin of the Psychonomic Society*, *6*(5), 465–468.

Ktori, M., & Pitchford, N. J. (2008). Effect of orthographic transparency on letter position encoding: A comparison of greek and english monoscriptal and biscriptal readers. *Language and Cognitive Processes*, *23*(2), 258–281.

Kuo, W.-J., Yeh, T.-C., Lee, C.-Y., Wu, Y.-T., Chou, C.-C., Ho, L.-T., Hung, D. L., Tzeng, O. J., & Hsieh, J.-C. (2003). Frequency effects of chinese character processing in the brain: An event-related fmri study. *Neuroimage*, *18*(3), 720–730.

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. (2017). Lmertest package: Tests in linear mixed effects models. *Journal of statistical software*, *82*(13), 1–26.

Kwon, M., Legge, G. E., & Dubbels, B. R. (2007). Developmental changes in the visual span for reading. *Vision research*, *47*(22), 2889–2900.

Lavric, A., Elchlepp, H., & Rastle, K. (2012). Tracking hierarchical processing in morphological decomposition with brain potentials. *Journal of Experimental Psychology: Human Perception and Performance*, *38*(4), 811.

Lee, A. L., Liu, Z., & Lu, H. (2021). Parts beget parts: Bootstrapping hierarchical object representations through visual statistical learning. *Cognition*, *209*, 104515.

Lee, M. D., & Wagenmakers, E.-J. (2014). *Bayesian cognitive modeling: A practical course*. Cambridge university press.

Lehtonen, M., Monahan, P. J., & Poeppel, D. (2011). Evidence for early morphological decomposition: Combining masked priming with magnetoencephalography. *Journal of cognitive neuroscience*, *23*(11), 3366–3379.

Lelonkiewicz, J. R., Ktori, M., & Crepaldi, D. (2020). Morphemes as letter chunks: Discovering affixes through visual regularities. *Journal of Memory and language*, *115*, 104152.

Leminen, A., Jakonen, S., Leminen, M., Mäkelä, J. P., & Lehtonen, M. (2016). Neural mechanisms underlying word-and phrase-level morphological parsing. *Journal of Neurolinguistics*, *38*, 26–41.

Leminen, A., Leminen, M., Kujala, T., & Shtyrov, Y. (2013). Neural dynamics of inflectional and derivational morphology processing in the human brain. *Cortex*, *49*(10), 2758–2771.

Leminen, A., Smolka, E., Dunabeitia, J. A., & Pliatsikas, C. (2019). Morphological processing in the brain: The good (inflection), the bad (derivation) and the ugly (compounding). *cortex*, *116*, 4–44.

Lengyel, G., Nagy, M., & Fiser, J. (2021). Statistically defined visual chunks engage object-based attention. *Nature communications*, *12*(1), 1–12.

Lengyel, G., Žalalytė, G., Pantelides, A., Ingram, J. N., Fiser, J., Lengyel, M., & Wolpert, D. M. (2019). Unimodal statistical learning produces multimodal object-like representations. *Elife*, *8*, e43942.

Lenth, R. (2019). Emmeans: Estimated marginal means, aka least-square means. *R package version*, *1*(4), 2.

Leppink, J., O'sullivan, P., & Winston, K. (2017). Evidence against vs. in favour of a null hypothesis. *Perspectives on medical education*, *6*(2), 115.

Levi, D. M. (2008). Crowding—an essential bottleneck for object recognition: A mini-review. *Vision research*, *48*(5), 635–654.

Lewis, G., Solomyak, O., & Marantz, A. (2011). The neural basis of obligatory decomposition of suffixed words. *Brain and language*, *118*(3), 118–127.

Lin, S.-E., Chen, H.-C., Zhao, J., Li, S., He, S., & Weng, X.-C. (2011). Left-lateralized n170 response to unpronounceable pseudo but not false chinese characters—the key role of orthography. *Neuroscience*, *190*, 200–206.

Liu-Shuang, J., Norcia, A. M., & Rossion, B. (2014). An objective index of individual face discrimination in the right occipito-temporal cortex by means of fast periodic oddball stimulation. *Neuropsychologia*, *52*, 57–72.

Liu-Shuang, J., Torfs, K., & Rossion, B. (2016). An objective electrophysiological marker of face individualisation impairment in acquired prosopagnosia with fast periodic visual stimulation. *Neuropsychologia*, *83*, 100–113.

Lobier, M., Dubois, M., & Valdois, S. (2013). The role of visual processing speed in reading speed development. *PloS one*, *8*(4), e58097.

Lochy, A., Jacques, C., Maillard, L., Colnat-Coulbois, S., Rossion, B., & Jonas, J. (2018). Selective visual representation of letters and words in the left ventral occipito-temporal cortex with intracerebral recordings. *Proceedings of the National Academy of Sciences*, *115*(32), E7595–E7604.

Lochy, A., Van Belle, G., & Rossion, B. (2015). A robust index of lexical representation in the left occipito-temporal cortex as evidenced by eeg responses to fast periodic visual stimulation. *Neuropsychologia*, *66*, 18–31.

Lochy, A., Van Reybroeck, M., & Rossion, B. (2016). Left cortical specialization for visual letter strings predicts rudimentary knowledge of letter-sound association in preschoolers. *Proceedings of the National Academy of Sciences*, *113*(30), 8544–8549.

Longtin, C.-M., & Meunier, F. (2005). Morphological decomposition in early visual word processing. *Journal of Memory and Language*, *53*(1), 26–41.

Longtin, C.-M., Segui, J., & Hallé, P. A. (2003). Morphological priming without morphological relationship. *Language and cognitive processes*, *18*(3), 313–334.

Manassi, M., & Whitney, D. (2018). Multi-level crowding and the paradox of object recognition in clutter. *Current Biology*, *28*(3), R127–R133.

Marcet, A., Ghukasyan, H., Fernández-López, M., & Perea, M. (2020). Jalapeno or jalapeño: Do diacritics in consonant letters modulate visual similarity effects during word recognition? *Applied Psycholinguistics*, *41*(3), 579–593.

Marelli, M., Amenta, S., & Crepaldi, D. (2015). Semantic transparency in free stems: The effect of orthography-semantics consistency on word recognition. *Quarterly Journal of Experimental Psychology*, *68*(8), 1571–1583.

Marelli, M., Amenta, S., Morone, E. A., & Crepaldi, D. (2013). Meaning is in the beholder's eye: Morpho-semantic effects in masked priming. *Psychonomic bulletin & review*, *20*(3), 534–541.

Marelli, M., & Baroni, M. (2015). Affixation in semantic space: Modeling morpheme meanings with compositional distributional semantics. *Psychological review*, *122*(3), 485.

Marino, C., Bernard, C., & Gervain, J. (2020). Word frequency is a cue to lexical category for 8-month-old infants. *Current Biology*.

Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of eeg- and meg-data. *Journal of neuroscience methods*, *164*(1), 177–190.

Mason, M. (1975). Reading ability and letter search time: Effects of orthographic structure defined by single-letter positional frequency. *Journal of Experimental Psychology: General*, *104*(2), 146.

Mason, M. (1978). From print to sound in mature readers as a function of reader ability and two forms of orthographic regularity. *Memory & Cognition*, *6*(5), 568–581.

Mason, M. (1982). Recognition time for letters and nonletters: Effects of serial position, array size, and processing order. *Journal of Experimental Psychology: Human Perception and Performance*, *8*(5), 724.

Mason, M., & Katz, L. (1976). Visual processing of nonlinguistic strings: Redundancy effects and reading ability. *Journal of Experimental Psychology: General*, *105*(4), 338.

Massaro, D. W., Jastrzembski, J. E., & Lucas, P. A. (1981). Frequency, orthographic regularity, and lexical status in letter and word perception. *Psychology of learning and motivation* (pp. 163–200). Elsevier.

Masson, M. E., & Bodner, G. E. (2003). A retrospective view of masked priming: Toward a unified account of masked and long-term repetition priming. *Masked priming: The state of the art*, 57–94.

Maye, J., Weiss, D. J., & Aslin, R. N. (2008). Statistical phonetic learning in infants: Facilitation and feature generalization. *Developmental science*, *11*(1), 122–134.

Maye, J., Werker, J. F., & Gerken, L. (2002). Infant sensitivity to distributional information can affect phonetic discrimination. *Cognition*, *82*(3), B101–B111.

McClelland, J. L., & Rumelhart, D. E. (1981). An interactive activation model of context effects in letter perception: I. an account of basic findings. *Psychological review*, *88*(5), 375.

McConkie, G. W., Kerr, P. W., Reddix, M. D., Zola, D., & Jacobs, A. M. (1989). Eye movement control during reading: Ii. frequency of refixating a word. *Perception & Psychophysics*, *46*(3), 245–253.

McCormick, S. F., Brysbaert, M., & Rastle, K. (2009). Short article: Is morphological decomposition limited to low-frequency words? *Quarterly Journal of Experimental Psychology*, *62*(9), 1706–1715.

McDonald, S. A., & Shillcock, R. C. (2003). Low-level predictive inference in reading: The influence of transitional probabilities on eye movements. *Vision Research*, *43*(16), 1735–1751.

Medvedovsky, M., Taulu, S., Bikmullina, R., Ahonen, A., & Paetau, R. (2009). Fine tuning the correlation limit of spatio-temporal signal space separation for magnetoencephalography. *Journal of neuroscience methods*, *177*(1), 203–211.

Merikle, P. M., Lowe, D. G., & Coltheart, M. (1971). Familiarity and method of report as determinants of tachistoscopic performance. *Canadian Journal of Psychology/Revue canadienne de psychologie*, *25*(2), 167.

Michimata, C., & Hellige, J. B. (1987). Effects of blurring and stimulus size on the lateralized processing of nonverbal stimuli. *Neuropsychologia*, *25*(2), 397–407.

Mirman, D., & Magnuson, J. S. (2009). Dynamics of activation of semantically similar concepts during spoken word recognition. *Memory & cognition*, *37*(7), 1026–1039.

Monsell, S., Doyle, M. C., & Haggard, P. N. (1989). Effects of frequency on visual word recognition tasks: Where are they? *Journal of Experimental Psychology: General*, *118*(1), 43.

Montani, V., Chanoine, V., Stoianov, I. P., Grainger, J., & Ziegler, J. C. (2019). Steady state visual evoked potentials in reading aloud: Effects of lexicality, frequency and orthographic familiarity. *Brain and Language*, *192*, 1–14.

Montani, V., Facoetti, A., & Zorzi, M. (2015). The effect of decreased interletter spacing on orthographic processing. *Psychonomic Bulletin & Review*, *22*(3), 824–832.

Morey, R. D., Rouder, J. N., & Jamil, T. (2015). Bayesfactor: Computation of bayes factors for common designs. r package version 0.9. 12-2.

Morgan, E., Fogel, A., Nair, A., & Patel, A. D. (2019). Statistical learning and gestalt-like principles predict melodic expectations. *Cognition*, *189*, 23–34.

Morris, J., Porter, J. H., Grainger, J., & Holcomb, P. J. (2011). Effects of lexical status and morphological complexity in masked priming: An erp study. *Language and cognitive processes*, *26*(4-6), 558–599.

Näätänen, R., Paavilainen, P., Rinne, T., & Alho, K. (2007). The mismatch negativity (mmn) in basic research of central auditory processing: A review. *Clinical neurophysiology*, *118*(12), 2544–2590.

Nazir, T. A., Ben-Boutayab, N., Decoppet, N., Deutsch, A., & Frost, R. (2004). Reading habits, perceptual learning, and recognition of printed words. *Brain and language*, *88*(3), 294–311.

Nazir, T. A., & Huckauf, A. (2007). The visual skill "reading". *Single-word reading* (pp. 39–56). Psychology Press.

New, B., & Grainger, J. (2011). On letter frequency effects. *Acta Psychologica*, *138*(2), 322–328.

Newport, E. L. (2016). Statistical language learning: Computational, maturational, and linguistic constraints. *Language and Cognition*, *8*(3), 447–461.

Newport, E. L., & Aslin, R. N. (2004). Learning at a distance i. statistical learning of non-adjacent dependencies. *Cognitive psychology*, *48*(2), 127–162.

Nickerson, R. S. (1965). Response times for “same”-“different” judgments. *Perceptual and Motor Skills*, *20*(1), 15–18.

Norcia, A. M., Appelbaum, L. G., Ales, J. M., Cottereau, B. R., & Rossion, B. (2015). The steady-state visual evoked potential in vision research: A review. *Journal of vision*, *15*(6), 4–4.

Obleser, J., Boecker, H., Drzezga, A., Haslinger, B., Hennenlotter, A., Roettinger, M., Eulitz, C., & Rauschecker, J. P. (2006). Vowel sound extraction in anterior superior temporal cortex. *Human brain mapping*, *27*(7), 562–571.

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J.-M. (2011). Fieldtrip: Open source software for advanced analysis of meg, eeg, and invasive electrophysiological data. *Computational intelligence and neuroscience*, *2011*.

Osborne, J. (2010). Improving your data transformations: Applying the box-cox transformation. *Practical Assessment, Research, and Evaluation*, *15*(1), 12.

Owsowitz, S. E. (1943). *The effects of word familiarity and letter structure familiarity on the perception of words* (tech. rep.). RAND CORP SANTA MONICA CA.

Paap, K. R., Newsome, S. L., & Noel, R. W. (1984). Word shape’s in poor shape for the race to the lexicon. *Journal of Experimental Psychology: Human perception and performance*, *10*(3), 413.

Pacton, S., Fayol, M., Nys, M., & Peereman, R. (2019). Implicit statistical learning of graphotactic knowledge and lexical orthographic acquisition. *Spelling and writing words* (pp. 41–66). Brill.

Pacton, S., Perruchet, P., Fayol, M., & Cleeremans, A. (2001). Implicit learning out of the lab: The case of orthographic regularities. *Journal of experimental psychology: General*, *130*(3), 401.

Pammer, K., Hansen, P. C., Kringelbach, M. L., Holliday, I., Barnes, G., Hillebrand, A., Singh, K. D., & Cornelissen, P. L. (2004). Visual word recognition: The first half second. *Neuroimage*, *22*(4), 1819–1825.

Pelli, D. G., Farell, B., & Moore, D. C. (2003). The remarkable inefficiency of word recognition. *Nature*, *423*(6941), 752–756.

Pelli, D. G., Palomares, M., & Majaj, N. J. (2004). Crowding is unlike ordinary masking: Distinguishing feature integration from detection. *Journal of vision*, *4*(12), 12–12.

Pelli, D. G., & Tillman, K. A. (2007). Parts, wholes, and context in reading: A triple dissociation. *PLoS One*, *2*(8), e680.

Pelli, D. G., Tillman, K. A., Freeman, J., Su, M., Berger, T. D., & Majaj, N. J. (2007). Crowding and eccentricity determine reading rate. *Journal of vision*, *7*(2), 20–20.

Pelucchi, B., Hay, J. F., & Saffran, J. R. (2009). Learning in reverse: Eight-month-old infants track backward transitional probabilities. *Cognition*, *113*(2), 244–247.

Peña, M., Bonatti, L. L., Nespor, M., & Mehler, J. (2002). Signal-driven computations in speech processing. *Science*, *298*(5593), 604–607.

Perea, M., Abu Mallouh, R., & Carreiras, M. (2010). The search for an input-coding scheme: Transposed-letter priming in arabic. *Psychonomic Bulletin & Review*, *17*(3), 375–380.

Perea, M., & Acha, J. (2009). Does letter position coding depend on consonant/vowel status? evidence with the masked priming technique. *Acta Psychologica*, *130*(2), 127–137.

Perea, M., Fernández-López, M., & Marcet, A. (2020). What is the letter é? *Scientific Studies of Reading*, *24*(5), 434–443.

Perea, M., Gomez, P., & Baciero, A. (2022). Do diacritics entail an early processing cost in the absence of abstract representations? evidence from masked priming in english.

Perea, M., Jiménez, M., Talero, F., & López-Cañada, S. (2015). Letter-case information and the identification of brand names. *British Journal of Psychology*, *106*(1), 162–173.

Perea, M., Moret-Tatay, C., & Gómez, P. (2011). The effects of interletter spacing in visual-word recognition. *Acta psychologica*, *137*(3), 345–351.

Perea, M., Panadero, V., Moret-Tatay, C., & Gómez, P. (2012). The effects of inter-letter spacing in visual-word recognition: Evidence with young normal readers and developmental dyslexics. *Learning and Instruction*, *22*(6), 420–430.

Perea, M., & Rosa, E. (2002). Does "whole-word shape" play a role in visual word recognition? *Perception & psychophysics*, *64*(5), 785–794.

Perruchet, P. (2019). What mechanisms underlie implicit statistical learning? transitional probabilities versus chunks in language learning. *Topics in cognitive science*, *11*(3), 520–535.

Perruchet, P., & Desaulty, S. (2008). A role for backward transitional probabilities in word segmentation? *Memory & cognition*, *36*(7), 1299–1305.

Perruchet, P., & Pacton, S. (2006). Implicit learning and statistical learning: One phenomenon, two approaches. *Trends in cognitive sciences*, *10*(5), 233–238.

Perruchet, P., Tyler, M. D., Galland, N., & Peereman, R. (2004). Learning nonadjacent dependencies: No need for algebraic-like computations. *Journal of Experimental Psychology: General*, *133*(4), 573.

Pinel, P., & Dehaene, S. (2010). Beyond hemispheric dominance: Brain regions underlying the joint lateralization of language and arithmetic to the left hemisphere. *Journal of Cognitive Neuroscience*, *22*(1), 48–66.

Pitchford, N. J., Ledgeway, T., & Masterson, J. (2008). Effect of orthographic processes on letter position encoding. *Journal of Research in Reading*, *31*(1), 97–116.

Plaut, D. C., McClelland, J. L., Seidenberg, M. S., & Patterson, K. (1996). *Understanding normal and impaired word reading: Computational principles in quasi-regular domains.* Psychology Press.

Preston, K. A. (1935). The speed of word perception and its relation to reading ability. *The Journal of General Psychology*, *13*(1), 199–203.

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.

Price, C. J., & Devlin, J. T. (2003). The myth of the visual word form area. *Neuroimage*, *19*(3), 473–481.

Price, C. J., & Devlin, J. T. (2011). The interactive account of ventral occipitotemporal contributions to reading. *Trends in cognitive sciences*, *15*(6), 246–253.

Price, C. J., McCrory, E., Noppeney, U., Mechelli, A., Moore, C., Biggio, N., & Devlin, J. T. (2006). How reading differs from object naming at the neuronal level. *Neuroimage*, *29*(2), 643–648.

Price, C. J., Wise, R., & Frackowiak, R. (1996). Demonstrating the implicit processing of visually presented words and pseudowords. *Cerebral cortex*, *6*(1), 62–70.

Prinzmetal, W. (1992). The word-superiority effect does not require a t-scope. *Perception & Psychophysics*, *51*(5), 473–484.

Proctor, R. W. (1981). A unified theory for matching-task phenomena. *Psychological Review*, *88*(4), 291.

Puce, A., Allison, T., Asgari, M., Gore, J. C., & McCarthy, G. (1996). Differential sensitivity of human visual cortex to faces, letterstrings, and textures: A functional magnetic resonance imaging study. *Journal of neuroscience*, *16*(16), 5205–5215.

Quian Quiroga, R., & Kreiman, G. (2010). Measuring sparseness in the brain: Comment on bowers (2009).

Radtke, E. L., Martens, U., & Gruber, T. (2021). The steady-state visual evoked potential (ssvep) reflects the activation of cortical object representations: Evidence from semantic stimulus repetition. *Experimental Brain Research*, *239*(2), 545–555.

Rajalingham, R., Kar, K., Sanghavi, S., Dehaene, S., & DiCarlo, J. J. (2020). The inferior temporal cortex is a potential cortical precursor of orthographic processing in untrained monkeys. *Nature communications*, *11*(1), 1–13.

Raschle, N. M., Chang, M., & Gaab, N. (2011). Structural brain alterations associated with dyslexia predate reading onset. *Neuroimage*, *57*(3), 742–749.

Rastle, K., & Coltheart, M. (2006). Is there serial processing in the reading system; and are there local representations? In S. Andrews (Ed.), *From inkmarks to ideas: Current issues in lexical processing* (pp. 3–24). Psychology Press.

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.

Rastle, K., & Davis, M. H. (2003). Reading morphologically complex words. *Masked priming: The state of the art*, 279–305.

Rastle, K., & Davis, M. H. (2008). Morphological decomposition based on the analysis of orthography. *Language and Cognitive Processes*, *23*(7-8), 942–971.

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.

Rayner, K., White, S. J., & Liversedge, S. (2006). Raeding wrods with jubmled lettres: There is a cost.

Reber, A. S. (1967). Implicit learning of artificial grammars. *Journal of verbal learning and verbal behavior*, *6*(6), 855–863.

Regan, D. (1966). Some characteristics of average steady-state and transient responses evoked by modulated light. *Electroencephalography and clinical neurophysiology*, *20*(3), 238–248.

Reicher, G. M. (1969). Perceptual recognition as a function of meaningfulness of stimulus material. *Journal of experimental psychology*, *81*(2), 275.

Retter, T. L., Jiang, F., Webster, M. A., & Rossion, B. (2018). Dissociable effects of inter-stimulus interval and presentation duration on rapid face categorization. *Vision research*, *145*, 11–20.

Retter, T. L., & Rossion, B. (2016). Uncovering the neural magnitude and spatio-temporal dynamics of natural image categorization in a fast visual stream. *Neuropsychologia*, *91*, 9–28.

Riesenhuber, M., & Poggio, T. (1999). Hierarchical models of object recognition in cortex. *Nature neuroscience*, *2*(11), 1019–1025.

Ripley, B., Venables, B., Bates, D. M., Hornik, K., Gebhardt, A., Firth, D., & Ripley, M. B. (2013). Package 'mass'. *Cran r*, *538*, 113–120.

Rolls, E. T. (2001). Functions of the primate temporal lobe cortical visual areas in invariant visual object and face recognition. *Vision: The Approach of Biophysics and Neurosciences*, 366–395.

Rosenholtz, R., Yu, D., & Keshvari, S. (2019). Challenges to pooling models of crowding: Implications for visual mechanisms. *Journal of vision*, *19*(7), 15–15.

Rosenthal, O., Fusi, S., & Hochstein, S. (2001). Forming classes by stimulus frequency: Behavior and theory. *Proceedings of the National Academy of Sciences*, *98*(7), 4265–4270.

Rossion, B. (2014). Understanding individual face discrimination by means of fast periodic visual stimulation. *Experimental Brain Research*, *232*(6), 1599–1621.

Rossion, B., Torfs, K., Jacques, C., & Liu-Shuang, J. (2015). Fast periodic presentation of natural images reveals a robust face-selective electrophysiological response in the human brain. *Journal of vision*, *15*(1), 18–18.

Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic bulletin & review*, *16*(2), 225–237.

Roy, A. (2012). A theory of the brain: Localist representation is used widely in the brain. *Frontiers in psychology*, *3*, 551.

Rudell, A. P., & Hu, B. (2000). Behavioral and brain wave evidence for automatic processing of orthographically regular letter strings. *Brain and language*, *75*(2), 137–152.

Rumelhart, D. E., & McClelland, J. L. (1982). An interactive activation model of context effects in letter perception: Ii. the contextual enhancement effect and some tests and extensions of the model. *Psychological review*, *89*(1), 60.

Rumelhart, D. E., & Siple, P. (1974). Process of recognizing tachistoscopically presented words. *Psychological review*, *81*(2), 99.

Saffran, J. R., Aslin, R. N., & Newport, E. L. (1996). Statistical learning by 8-month-old infants. *Science*, *274*(5294), 1926–1928.

Saffran, J. R., Johnson, E. K., Aslin, R. N., & Newport, E. L. (1999). Statistical learning of tone sequences by human infants and adults. *Cognition*, *70*(1), 27–52.

Saffran, J. R., & Kirkham, N. Z. (2018). Infant statistical learning. *Annual review of psychology*, *69*, 181–203.

Sanders, L. D., Newport, E. L., & Neville, H. J. (2002). Segmenting nonsense: An event-elated potential index of perceived onsets in continuous speech. *Nature Neuroscience*, *5*(7), 700–703.

Santolin, C., & Saffran, J. R. (2018). Constraints on statistical learning across species. *Trends in Cognitive Sciences*, *22*(1), 52–63.

Sawi, O. M., & Rueckl, J. (2019). Reading and the neurocognitive bases of statistical learning. *Scientific Studies of Reading*, *23*(1), 8–23.

Scaltritti, M., & Balota, D. A. (2013). Are all letters really processed equally and in parallel? further evidence of a robust first letter advantage. *Acta psychologica*, *144*(2), 397–410.

Scaltritti, M., Dufau, S., & Grainger, J. (2018). Stimulus orientation and the first-letter advantage. *Acta psychologica*, *183*, 37–42.

Scarf, D., Boy, K., Reinert, A. U., Devine, J., Güntürkün, O., & Colombo, M. (2016). Orthographic processing in pigeons (columba livia). *Proceedings of the National Academy of Sciences*, *113*(40), 11272–11276.

Schmalz, X., Altoè, G., & Mulatti, C. (2017). Statistical learning and dyslexia: A systematic review. *Annals of Dyslexia*, *67*(2), 147–162.

Schmalz, X., & Mulatti, C. (2017). Busting a myth with the bayes factor: Effects of letter bigram frequency in visual lexical decision do not reflect reading processes. *The Mental Lexicon*, *12*(2), 263–282.

Schubert, T. M., Cohen, T., & Fischer-Baum, S. (2020). Reading the written language environment: Learning orthographic structure from statistical regularities. *Journal of Memory and Language*, *114*, 104148.

Schwantes, F. M. (1978). Stimulus position functions in tachistoscopic identification tasks: Scanning, rehearsal, and order of report. *Perception & Psychophysics*, *23*(3), 219–226.

Seidenberg, M. S. (1987). Sublexical structures in visual word recognition: Access units or orthographic redundancy?

Seidenberg, M. S. (2005). Connectionist models of word reading. *Current directions in psychological science*, *14*(5), 238–242.

Sergent, J., & Hellige, J. B. (1986). Role of input factors in visual-field asymmetries. *Brain and Cognition*, *5*(2), 174–199.

Siegelman, N., Bogaerts, L., Kronenfeld, O., & Frost, R. (2018). Redefining "learning" in statistical learning: What does an online measure reveal about the assimilation of visual regularities? *Cognitive science*, *42*, 692–727.

Siegelman, N., & Frost, R. (2015). Statistical learning as an individual ability: Theoretical perspectives and empirical evidence. *Journal of memory and language*, *81*, 105–120.

Siegelman, N., Rueckl, J. G., Steacy, L. M., Frost, S. J., van den Bunt, M., Zevin, J. D., Seidenberg, M. S., Pugh, K. R., Compton, D. L., & Morris, R. D. (2020). Individual differences in learning the regularities between orthography, phonology and semantics predict early reading skills. *Journal of memory and language*, *114*, 104145.

Sliwinska, M. W., James, A., & Devlin, J. T. (2015). Inferior parietal lobule contributions to visual word recognition. *Journal of Cognitive Neuroscience*, *27*(3), 593–604.

Sloan, L. L. (1951). Measurement of visual acuity: A critical review. *AMA archives of ophthalmology*, *45*(6), 704–725.

Smith, F. (1969). The use of featural dependencies across letters in the visual identification of words. *Journal of Verbal Learning and Verbal Behavior*, *8*(2), 215–218.

Snell, J., & Theeuwes, J. (2020). A story about statistical learning in a story: Regularities impact eye movements during book reading. *Journal of Memory and Language*, *113*, 104127.

Sperlich, A., Meixner, J., & Laubrock, J. (2016). Development of the perceptual span in reading: A longitudinal study. *Journal of Experimental Child Psychology*, *146*, 181–201.

Spoehr, K. T., & Smith, E. E. (1973). The role of syllables in perceptual processing. *Cognitive Psychology*, *5*(1), 71–89.

Stacchi, L., Ramon, M., Lao, J., & Caldara, R. (2019). Neural representations of faces are tuned to eye movements. *Journal of Neuroscience*, *39*(21), 4113–4123.

Stefanics, G., Astikainen, P., & Czigler, I. (2015). Visual mismatch negativity (vmmn): A prediction error signal in the visual modality. *Frontiers in Human Neuroscience*, *8*, 1074.

Stefanics, G., Kremláček, J., & Czigler, I. (2014). Visual mismatch negativity: A predictive coding view. *Frontiers in human neuroscience*, *8*, 666.

Stein, J., & Fowler, S. (1981). Visual dyslexia. *Trends in Neurosciences*, *4*, 77–80.

Stevens, M., & Grainger, J. (2003). Letter visibility and the viewing position effect in visual word recognition. *Perception & Psychophysics*, *65*(1), 133–151.

Stothart, G., Quadflieg, S., & Milton, A. (2017). A fast and implicit measure of semantic categorisation using steady state visual evoked potentials. *Neuropsychologia*, *102*, 11–18.

Stothart, G., & Smith, L. (2020). A new functional biomarker of cognitive impairment in alzheimer's disease: Neuroimaging/optimal neuroimaging measures for early detection. *Alzheimer's & Dementia*, *16*, e041056.

Tadel, F., Baillet, S., Mosher, J. C., Pantazis, D., & Leahy, R. M. (2011). Brainstorm: A user-friendly application for meg/eeg analysis. *Computational intelligence and neuroscience*, *2011*.

Taft, M. (1979). Recognition of affixed words and the word frequency effect. *Memory & Cognition*, *7*(4), 263–272.

Taft, M. (1986). Lexical access codes in visual and auditory word recognition. *Language and Cognitive Processes*, *1*(4), 297–308.

Taft, M. (1992). The body of the boss: Subsyllabic units in the lexical processing of polysyllabic words. *Journal of Experimental Psychology: Human Perception and Performance*, *18*(4), 1004.

Taft, M. (1994). Interactive-activation as a framework for understanding morphological processing. *Language and cognitive processes*, *9*(3), 271–294.

Taft, M. (2004). Morphological decomposition and the reverse base frequency effect. *The Quarterly Journal of Experimental Psychology Section A*, *57*(4), 745–765.

Taft, M., & Forster, K. I. (1975). Lexical storage and retrieval of prefixed words. *Journal of verbal learning and verbal behavior*, *14*(6), 638–647.

Taft, M., & Forster, K. I. (1976). Lexical storage and retrieval of polymorphemic and polysyllabic words. *Journal of verbal learning and verbal behavior*, *15*(6), 607–620.

Taft, M., & Nguyen-Hoan, M. (2010). A sticky stick? the locus of morphological representation in the lexicon. *Language and Cognitive Processes*, *25*(2), 277–296.

Taulu, S., & Hari, R. (2009). Removal of magnetoencephalographic artifacts with temporal signal-space separation: Demonstration with single-trial auditory-evoked responses. *Human brain mapping*, *30*(5), 1524–1534.

Taulu, S., & Simola, J. (2006). Spatiotemporal signal space separation method for rejecting nearby interference in meg measurements. *Physics in Medicine & Biology*, *51*(7), 1759.

Taylor, J., 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.

Thesen, T., McDonald, C. R., Carlson, C., Doyle, W., Cash, S., Sherfey, J., Felsovalyi, O., Girard, H., Barr, W., Devinsky, O., et al. (2012). Sequential then interactive processing of letters and words in the left fusiform gyrus. *Nature communications*, *3*(1), 1–8.

Thiessen, E. D., Kronstein, A. T., & Hufnagle, D. G. (2013). The extraction and integration framework: A two-process account of statistical learning. *Psychological bulletin*, *139*(4), 792.

Townsend, J., Taylor, S., & Brown, D. (1971). Lateral masking for letters with unlimited viewing time. *Perception & Psychophysics*, *10*(5), 375–378.

Treiman, R., Gordon, J., Boada, R., Peterson, R. L., & Pennington, B. F. (2014). Statistical learning, letter reversals, and reading. *Scientific Studies of Reading*, *18*(6), 383–394.

Treiman, R., & Kessler, B. (2021). Statistical learning in word reading and spelling across languages and writing systems. *Scientific Studies of Reading*, 1–11.

Treisman, A., & Schmidt, H. (1982). Illusory conjunctions in the perception of objects. *Cognitive psychology*, *14*(1), 107–141.

Tseng, H., Lindsay, S., & Davis, C. J. (2020). Semantic interpretability does not influence masked priming effects. *Quarterly Journal of Experimental Psychology*, *73*(6), 856–867.

Turk-Browne, N. B., Jungé, J. A., & Scholl, B. J. (2005). The automaticity of visual statistical learning. *Journal of Experimental Psychology: General*, *134*(4), 552.

Turkeltaub, P. E., Gareau, L., Flowers, D. L., Zeffiro, T. A., & Eden, G. F. (2003). Development of neural mechanisms for reading. *Nature neuroscience*, *6*(7), 767–773.

Tydgat, I., & Grainger, J. (2009). Serial position effects in the identification of letters, digits, and symbols. *Journal of Experimental Psychology: Human Perception and Performance*, *35*(2), 480.

Uppenkamp, S., Johnsrude, I. S., Norris, D., Marslen-Wilson, W., & Patterson, R. D. (2006). Locating the initial stages of speech–sound processing in human temporal cortex. *Neuroimage*, *31*(3), 1284–1296.

Van den Berg, R., Roerdink, J. B., & Cornelissen, F. W. (2010). A neurophysiologically plausible population code model for feature integration explains visual crowding. *PLoS computational biology*, *6*(1), e1000646.

Van den Bussche, E., Van den Noortgate, W., & Reynvoet, B. (2009). Mechanisms of masked priming: A meta-analysis. *Psychological bulletin*, *135*(3), 452.

Van der Donck, S., Dzhelyova, M., Vettori, S., Mahdi, S. S., Claes, P., Steyaert, J., & Boets, B. (2020). Rapid neural categorization of angry and fearful faces is specifically impaired in boys with autism spectrum disorder. *Journal of Child Psychology and Psychiatry*.

van de Walle de Ghelcke, A., Rossion, B., Schiltz, C., & Lochy, A. (2020). Impact of learning to read in a mixed approach on neural tuning to words in beginning readers. *Frontiers in psychology*, *10*, 3043.

Van Zandt, T., Colonius, H., & Proctor, R. W. (2000). A comparison of two response time models applied to perceptual matching. *Psychonomic bulletin & review*, *7*(2), 208–256.

Vankov, I. I., & Bowers, J. S. (2017). Do arbitrary input–output mappings in parallel distributed processing networks require localist coding? *Language, Cognition and Neuroscience*, *32*(3), 392–399.

Velan, H., & Frost, R. (2009). Transposition effects are not universal: The impact of transposing letters in hebrew. *Journal of Memory and Language*, *61*(3), 285–302.

Verleger, R., Dittmer, M., & Śmigasiewicz, K. (2013). Cooperation or competition of the two hemispheres in processing characters presented at vertical midline. *PloS one*, *8*(2), e57421.

Verleger, R., Śmigasiewicz, K., & Möller, F. (2011). Mechanisms underlying the left visual-field advantage in the dual stream rsvp task: Evidence from n2pc, p3, and distractor-evoked veps. *Psychophysiology*, *48*(8), 1096–1106.

Vernet, M., Bellocchi, S., Leibnitz, L., Chaix, Y., & Ducrot, S. (2021). Predicting future poor readers from pre-reading visual skills: A longitudinal study [PMID: 33730530]. *Applied Neuropsychology: Child*, *0*(0), 1–15. https://doi.org/10.1080/21622965.2021.1895790

Vidal, C., & Chetail, F. (2017). Bacs: The brussels artificial character sets for studies in cognitive psychology and neuroscience. *Behavior Research Methods*, *49*(6), 2093–2112.

Vidal, Y., Viviani, E., Zoccolan, D., & Crepaldi, D. (2021). A general-purpose mechanism of visual feature association in visual word identification and beyond. *Current Biology*, *31*(6), 1261–1267.

Vigliocco, G., Warren, J., Siri, S., Arciuli, J., Scott, S., & Wise, R. (2006). The role of semantics and grammatical class in the neural representation of words. *Cerebral Cortex*, *16*(12), 1790–1796.

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.

von Koss Torkildsen, J., Arciuli, J., & Wie, O. B. (2019). Individual differences in statistical learning predict children's reading ability in a semi-transparent orthography. *Learning and individual differences*, *69*, 60–68.

Wang, F., Kaneshiro, B., Strauber, C. B., Hasak, L., Nguyen, Q. T. H., Yakovleva, A., Vildavski, V. Y., Norcia, A. M., & McCandliss, B. D. (2021). Distinct neural sources underlying visual word form processing as revealed by steady state visual evoked potentials (ssvep). *Scientific reports*, *11*(1), 1–15.

Warrington, E. K., & Shallice, T. (1980). Word-form dyslexia. *Brain: a journal of neurology*, *103*(1), 99–112.

Weiss, Y., Katzir, T., & Bitan, T. (2015). Many ways to read your vowels—neural processing of diacritics and vowel letters in hebrew. *NeuroImage*, *121*, 10–19.

Wertheim, T. (1894). Uber die indirekte sehscharfe. *Zeitschrift fur Psychologie*, *7*, 172–187.

Wheeler, D. D. (1970). Processes in word recognition. *Cognitive Psychology*, *1*(1), 59–85.

Whitney, C. (2001). How the brain encodes the order of letters in a printed word: The seriol model and selective literature review. *Psychonomic Bulletin & Review*, *8*(2), 221–243.

Whitney, D., & Levi, D. M. (2011). Visual crowding: A fundamental limit on conscious perception and object recognition. *Trends in cognitive sciences*, *15*(4), 160–168.

Wimmer, H., Ludersdorfer, P., Richlan, F., & Kronbichler, M. (2016). Visual experience shapes orthographic representations in the visual word form area. *Psychological Science*, *27*(9), 1240–1248.

Winskel, H., Ratitamkul, T., & Perea, M. (2018). Can the first letter advantage be shaped by script-specific characteristics? *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *44*(3), 493.

Wydell, T. N., Vuorinen, T., Helenius, P., & Salmelin, R. (2003). Neural correlates of letter-string length and lexicality during reading in a regular orthography. *Journal of Cognitive Neuroscience*, *15*(7), 1052–1062.

Yablonski, M., & Ben-Shachar, M. (2016). The morpheme interference effect in hebrew: A generalization across the verbal and nominal domains. *The Mental Lexicon*, *11*(2), 277–307.

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.

Zhao, L., Cosman, J. D., Vatterott, D. B., Gupta, P., & Vecera, S. P. (2014). Visual statistical learning can drive object-based attentional selection. *Attention, Perception, & Psychophysics*, *76*(8), 2240–2248.