The Front End of Visual Word Recognition: Exploring Hierarchical Representations during Skilled Reading

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DECLARATION OF AUTHORSHIP

I, Clare Lally, hereby declare that this work was carried out in accordance with the regulations of the University of London. I declare that this submission is my own work, and to the best of my knowledge does not represent the work of others, published or unpublished, except where duly acknowledged in the text. No part of this thesis has been submitted for a higher degree at another university or institution.

Signed: C.F. Lally

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ABSTRACT

The processes that contribute to visual word recognition are highly versatile. Successful recognition is achieved via a complex set of interacting cognitive processes, which are co-adapted from existing neuro-biological structures and shaped in response to the written environment. The overarching aim of this thesis was to better understand the nature and deployment of representations that arise during the early stages of word reading. The studies reported investigated both short-term situational factors that influence how readers weight orthographic information 'in the moment', as well as properties of the writing system that mould long-term representations over years of acquisition. The first half of this thesis investigated how letter identification is modulated online by surrounding orthographic and sentence context. The findings consistently indicated that letter identification processes are signal-contingent, as readers determine the precision of lower-level processing required based on cues from higher-level knowledge. Critically, the influence of surrounding orthographic information extends beyond individual word boundaries to mediate sub-lexical processing of other words within a sentence. The second half of this thesis focused on how weighting attributed to various orthographic cues emerges from long-term experience with the writing system. Our artificial language learning paradigm demonstrated that weightings assigned to various sources of orthographic information vary cross-linguistically, as they are shaped by salient characteristics of the written environment. In addition, we established partial MRI evidence that readers form neural representations for statistically salient letter combinations, such as those associated with morphemes. Overall, this thesis demonstrates that word recognition is achieved in a variable adaptive manner, as readers dynamically weight different sources of orthographic information based on immediate short-term context and long-standing knowledge of the writing system.

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CHAPTER ONE: INTRODUCTION

Reading is a remarkable human skill that enables us to rapidly transform arbitrary visual symbols into meaningful linguistic information, such as the meanings and pronunciations of words. It is essential for participating in most modern societies, and it is ingrained in our everyday activities. Skilled reading becomes fluent and autonomous; therefore, it is easy to overlook the cognitive acrobatics required for this remarkable feat. The underlying cognitive processes are of particular interest because humans do not have an inborn capacity for reading. Unlike spoken language, reading is a culturally learned skill, which requires years of formal instruction to master. Therefore, reading is a prime example of a highly complex skill that draws upon existing cognitive structures and adapts based on properties of the environment (i.e. the writing system). Perhaps the most fundamental question within reading research is how readers recognise printed words. As I demonstrate below, a rich body of literature indicates that single word reading involves multiple levels of representation. Notably, orthographic knowledge plays a critical role in how salient information is weighted for efficient word recognition.

Researchers typically investigate influences on word recognition in carefully controlled designs that enable specific processes to be studied in isolation. However, readers do not necessarily assign the same weight to different cues each time they recognise a word. This thesis highlights the consequences of studying reading processes as component parts, and how the overall picture might change when we consider how these processes interact or vary across instances of word recognition. Word recognition is a dynamic process shaped by the environment, and understanding the factors that contribute to this is essential for a fully integrated account of reading. This thesis aims to achieve this goal, by investigating how skilled readers hierarchically integrate the various cues that arise during the early stages visual word recognition. I focus upon how information is weighted based on properties of the writing system and the context available.

1.1 The hierarchical nature of reading

Word recognition involves the orchestration of various stages of information processing, whereby different levels of representation must be integrated in order to crack this orthographic code. A useful way to think about this is to consider some of the challenges that readers encounter at various stages within an imperfect writing system, outlined below.

1.1.1 Letter identification

There is consensus that words are recognised through the analysis of their component letters. The visual appearance of letters can be highly variable depending on characteristics such as case and font. For example, *rage* and *RAGE* refer to the same word containing the exact same letters, yet they are visually very dissimilar. In contrast, *RAGE* and *PACE* look similar, but contain different letters and hence refer to different words. Therefore, readers must maintain enough flexibility to associate different letter shapes with the same identity ("telling together"[1], e.g. *R*-*r*), but also enough precision to distinguish between visually similar letter shapes that refer to different letter identities ("telling apart", e.g. *R*-*B*).

[1] This phrase is not typically used when describing letter identification. I have borrowed it from the face processing (Burton, 2013) and voice processing literature (Lavan et al., 2019).

CHAPTER 1: INTRODUCTION

Readers are remarkably tolerant of visual variability when telling letters together. Skilled readers can identify a briefly displayed letter without being able to recall whether the letter was presented in upper or lower case (Adams, 1979; Coltheart & Freeman, 1974; Friedman, 1980; McClelland, 1976), and cross-case priming facilitation occurs independently of visual similarity (e.g. *kiss – KISS* vs. *edge – EDGE*; Bowers et al., 1998; Kinoshita & Kaplan, 2008). Readers are thought to tolerate within-letter variation by rapidly mapping the veridical visual form of letter shapes to abstract letter identities, invariant of feature disparities such as case or font (Davis, 2012; Dehaene et al., 2005; Gomez et al., 2008; Rothlein & Rapp, 2014).

Whilst visual feature information does not appear to impede readers' ability to tell letters together, it does influence readers' ability to tell letters apart. Word recognition is facilitated by prior presentation of stimuli that contain visually similar letters (*dentjst-DENTIST vs. dentgst-DENTIST,* Marcet & Perea, 2017*; docurnent–DOCUMENT* vs. *docusnent–DOCUMENT*; Marcet & Perea, 2018), numbers (*C4BLE-cable* vs. *C9BLE-cable;* Kinoshita et al., 2013; Lien et al., 2014; Perea et al., 2008) and symbols (*C△BLE-CABLE;* Perea et al., 2008). Visual similarity effects suggest that readers tentatively encode letter identities based on their correspondence to visual feature information, allowing an initial degree of uncertainty between letter identities which is resolved as information is accumulated (Norris & Kinoshita., 2012; Marcet & Perea, 2017). Together, these explanations of telling together and telling apart provide a converging account of how readers may maintain the balance of flexibility and precision when assigning letter identities. Readers initially identify letters through the assembly of low-level visual information and consolidation from orthographic knowledge of letter shapes, at which stage they are mapped onto abstract letter identities.

One critical feature of letters is that they are typically assembled to form a part of a letter string. There is substantial evidence that letter identification is not solely guided by properties of the individual letter, but also by surrounding letters within the string. Readers are more accurate at identifying letters when they appear in the context of a real word compared to a pseudoword, known as the word superiority effect (e.g. *crown* vs. *crowl;* Coch & Mitra, 2010; Grainger & Jacobs, 1994; Kezilas et al., 2016; Reicher, 1969; Wheeler, 1970). Letter identification is also more accurate in pronounceable pseudowords compared to unpronounceable consonant strings (*crowl* vs. *crtwl*; Baron & Thurston, 1973; Carr et al., 1978), termed the pseudoword superiority effect. Combined, these findings suggest that letter identification processes are enhanced by readers' existing word representations and knowledge of orthotactic constraints (i.e. restrictions on how letters combine within a writing system; Kezilas et al., 2016). In addition, these effects display that the contexts in which letters appear can significantly alter readers' ability to discriminate between them.

1.1.2 Letter position coding

Readers must also be able to distinguish between words consisting of the same letter combinations, such as *slate*, *stale* and *steal*. Therefore, readers must assign positional information, as well as identity information, to each letter. The simplest way to model letter position is through slot coding, in which letter identity and position are encoded together, for example with letter position coded relative to the start of the word (e.g. slate = $S_1\,L_2\,A_3\,T_4\,E_5$; McClelland & Rumelhart, 1981). However, substantial evidence suggests that letter position is encoded with greater flexibility than slot coding allows. This has been widely observed through the transposed-letter effect, which demonstrates that there is greater perceptual similarity between stimuli that comprise the same letters in different positions (*jugde-judge*), compared to stimuli in which the equivalent letters are substituted (*jupke-judge*, Andrews, 1996; Chambers, 1979; Lupker et al., 2008; Perea & Lupker, 2003; Perea & Lupker, 2004; Schoonbaert & Grainger, 2004). Transposed-letter effects indicate that lexical representations of words can be activated with imprecise positional information. These effects pose a challenge for the rigidity of position-specific coding schemes, which would predict that letter transpositions and letter substitutions result in the same degree of perceptual similarity with their base word. For example, *jugde* ($J_1U_2G_3D_4E_5$) and *jupke* ($J_1U_2P_3K_4E_5$) both share three letters in the same position with *judge* ($J_1U_2D_3G_4E_5$).

The transposed-letter effect has inspired a variety of competing theories that allow for flexibility within letter position coding. The Open Bigram model proposes that readers code letter pairs in terms of their relative order within the word (*judge: JU, JD. JG, JE, UD, UG, UE, DG, DE, GE*, Whitney, 2001; Grainger & Whitney, 2004), with transposed-letters resulting in greater facilitation as they share more bigrams with the target. The overlap model predicts that positional information is normally distributed over letter identities and leaks into nearby letters (Gomez et al., 2008). For example, the letter *g* in *judge* is associated with Position 4, and to a lesser extent adjacent positions 3 and 5. If the letter identity is different, then there is no facilitation from overlapping positional information. In spatial coding schemes, letter identities are coded independently of position as switched-on letter nodes (Davis 1999; Davis, 2010), which emit different activation levels based on letter position within the word. Therefore, anagrams activate the same letter nodes but produce different spatial patterns of activity. Letter transpositions have greater perceptual similarity than letter substitutions, as substitutions activate different letter nodes.

As with letter identity, it is important to consider how letter position coding may be influenced by readers' lexical knowledge of existing words. Some letter position coding schemes have been incorporated in the role of lexical representations in establishing letter positions. For example, the SERIOL model (Whitney, 2001) posits that bigram nodes send excitatory activation to corresponding word nodes. Similarly, the SOLAR model (Davis, 2010) implements spatial coding and includes a word-matching scheme in which the spatial patterns of activated letter nodes are compared to spatial patterns of existing words within the lexicon.

1.1.3 Sub-lexical units

Thus far, we have considered how readers identify individual letters and establish the order in which they appear. On the simplest level, letters constitute the building blocks of words. However, there may be intermediate levels of representation between letters and words, as letters can be combined to form functional orthographic structures that denote part of a word's pronunciation or meaning.

In alphabetic languages such as English, letters act as graphemes that represent phonemes (sounds). For example, the word *blend* contains five graphemes that represent the five sounds within the word *(/b-l-e-n-d/*). However, graphemes and phonemes do not necessarily have a one-to-one mapping, as a grapheme can consist of multiple letters. For example, the word *though* consists of six letters, but only two graphemes (*th-ough* = /*ð-oʊ*/). Evidence suggests that skilled readers form sub-lexical representations for multiple-letter graphemes, as readers are less accurate at detecting letters within multiple letter graphemes (*break)* compared to single letter graphemes (*brick;* Rey et al., 2000). Word recognition can also influenced by other phonological sub-lexical units, such as syllables, although there is debate as to whether this only apparent for words in languages with regular syllabic structures (see Chetail & Content, 2012; Chetail & Content, 2013; Chetail & Mathey, 2009). In Spanish, readers recognise words more quickly when they are preceded by a pseudoword with the same first syllable (*junas-JUNIO)*, relative to a pseudoword with the same proportion of letters (*juntu-JUNIO*; Álvarez et al., 2004; Carreiras & Perea, 2002). Pseudowords are also harder to reject in a lexical decision task and have shorter naming latencies if they contain high frequency syllables (Perea & Carreiras, 1998; Carreiras & Perea, 2004).

Words can also contain sub-lexical units that denote meaning. Relationships between print and meaning are reflected in morphology, with morphemes defined as the smallest meaningful unit in a word. Words are classed as mono-morphemic when the word itself is the smallest unit of meaning (e.g. *lock*). However, morphologically complex words can be further parsed into meaningful components. Words are embedded as stems, appended by affixes that modify the meanings of words in a highly predictable manner (*unlock, lockable, locker*). Evidence suggests that readers rapidly decompose letter strings into their morphemic constituents (*un-lock*, see Rastle, 2019b for a review). Masked-priming demonstrates that morphologically complex words facilitate faster recognition of their stem (*teacher-TEACH*) compared with non-morphological words with equivalent orthographic overlap (*window-WIND*; Rastle et al., 2004). Notably, this benefit extends to words that have a pseudo-morphological structure but no semantic connection (*corner-CORN*; Beyersmann et al., 2012; Beyersman et al., 2016; Meunier & Longtin, 2007; Marslen-Wilson et al., 2008; Morris et al., 2007; Rastle & Davis, 2008; Rastle et al., 2004). This suggests that readers decompose any word with a plausible morphological structure (Rastle et al., 2004). Therefore, there is substantial evidence that readers form sub-lexical representations for morphemes, which may play a crucial role in mapping print to meaning.

The examples above demonstrate intermediate levels of representation between individual letters and entire words. Various sub-lexical structures have a discernible influence on reading behaviour, which suggests that readers utilise this information during visual word recognition. Therefore, any comprehensive theory of reading must be able to account for how sub-lexical units are processed. However, integration of sub-lexical processing introduces additional complications. Sub-lexical units cannot simply be regarded as independent component parts, as they can change how the entire word is processed. For example, syllable properties modify word pronunciations, such as vowel reduction and stress assignment (Mousikou et al., 2017). Further, some sub-lexical units may have greater salience compared with others, such as morphemes (Rastle, 2019b). In addition, there is evidence that letter-level perceptual effects can migrate across sub-lexical units. For example, transposed-letter effects occur regardless of whether transpositions violate graphemic letter combination rules (Guerrera & Forster, 2008) and cross syllable boundaries (Perea & Lupker, 2003). Therefore, understanding how readers integrate information from sub-lexical representations is a key part of the puzzle in understanding the processes that underpin visual word recognition.

1.1.4 Relationships between words

Sub-lexical processes are guided by lexical knowledge, which refers to readers' knowledge of existing words within their vocabulary (the lexicon). As outlined above, the word superiority effect demonstrates that lexical knowledge enhances the perceptibility of individual letters. Word recognition is not only influenced by whether a reader is familiar with a particular word, but also by their knowledge of related words. One of the biggest influences on the accuracy and speed of word recognition is frequency (how often a reader encounters a word). High frequency words are reliably processed faster than low frequency words in a variety of tasks, including lexical decision and word naming tasks (Forster & Chambers, 1973; see Brysbaert et al., 2018 for a review). Word frequency exerts such a powerful influence over word recognition that it is estimated to account for 30-40% of variance in word recognition tasks (Brysbaert et al., 2016). This suggests either that frequently encountered words have more robust lexical representations, or that such representations are prioritised as they have a higher likelihood of occurring. More broadly, word frequency effects demonstrate that words are not recognised with equivalent ease.

Word recognition is also influenced by other known words that are orthographically, semantically or phonologically related. A prominent example is how word recognition is modulated by orthographic neighbourhood effects (Coltheart et al., 1977). Orthographic neighbours are words that are the same length but differ by only one letter (e.g. *clash-crash*). Neighbourhood density (the number of orthographic neighbours belonging to a word) can have a facilitative effect on word recognition. Low frequency words with many neighbours are recognised faster than those with few neighbours (Andrews, 1989), and pseudowords with many word neighbours take longer to reject in lexical decision tasks (Coltheart et al., 1977). However, word neighbours can introduce competition effects and delay recognition if they have a higher frequency than the target (Grainger, 1990; Grainger & Segui, 1990). This example denotes a common theme within this thesis, a particular property of a word (in this case, high orthographic density) may beneficial for some cases of word recognition, but not necessarily in all cases of word recognition. Readers often encounter words in which there are multiple cues, which may outweigh each other based on based on other orthographic information available.

Visual word recognition is further influenced by words that are phonologically and semantically related. Readers take longer to recognise homophones as real words (e.g. *weight-wait*, Ferrand & Grainger, 2003; Pexman et al., 2001) and find it harder to reject pseudoword homophones that have the same pronunciations as real words (e.g. *hite,* Ferrand & Grainger, 2003; Ziegler et al., 2001a). These findings indicate that word recognition is subject to interference from competing words with overlapping phonological information. Masked-priming paradigms demonstrate that words are recognised faster when preceded by a semantically related word (*fast-quick*) compared to an unrelated word (*fast-quiet*; see Neely, 2012, for a review). It is suggested that word activation spreads to related words within a semantic network, therefore, semantically related words are recognised faster as they are already partially activated from the prime. Semantic effects are also evident in words that are spelled the same but have multiple meanings. Homonyms with multiple unrelated meanings (*bark*) are typically recognised more slowly and less accurately than words with a single unambiguous meaning (Armstrong & Plaut, 2016; Hino et al., 2006), whereas polysemous words with multiple related meanings (*run*) are recognised faster and with greater accuracy than unambiguous words (Klepousniotou et al., 2008; Rodd et al., 2002).

In summary, word recognition is routinely modulated by connections between other words within the lexicon. These connections can induce facilitation as well as interference based on various overlapping orthographic, phonological and semantic properties, and how they interact with each other.

1.1.5 Words in context

If letters are the building blocks of words, words are the building blocks of sentences (Grainger & Hannagan, 2014). Reading is rarely restricted to words in isolation, as words can be combined to convey more complex messages. Thus, readers must also be able to understand how words relate to each other in a sentence. Sentence context can provide additional information during word recognition. For example, we can use wider context to infer between multiple word meanings (*the cricket team bought new bats/the caves were inhabited by bats*, see Blott et al., 2020), or to deduce the intended word from a spelling error (*the barber combed his berad/the baker sliced his berad*).

Readers routinely integrate sentence level information during word recognition. They are better at recalling grammatical sentences compared to the same words in a jumbled order (Baddeley et al., 2009, Toyota, 2001), and more accurate at recognising words in grammatical sentences compared to ungrammatical sentences (Snell & Grainger, 2017). Whilst readers demonstrate sensitivity to grammaticality, they also appear to demonstrate flexibility in sentence word order, in a similar manner to the transposed letter effect. For example, readers are less likely to notice transposed word effects if the words can be re-arranged to form a grammatical sentence (e.g. *the old was tortoise slow* vs. *the old was tortoise quietly*, Mirault et al., 2018; Pegado & Grainger, 2019, 2020, 2021; Snell & Grainger, 2019; Wen et al., 2021). As well as syntactic plausibility, word recognition is also facilitated by semantic predictability from sentence context. Readers are more accurate at identifying words in a semantically plausible context compared to an implausible context (*I write a column to be published in a newspaper/vegetable*; Asano & Yokosawa, 2011).

Eye-tracking has played a pivotal role in understanding online processing during sentence reading, particularly how syntactic information is integrated (see Clifton & Staub, 2011 for a review), and how eye-movements are driven by semantic predictability (see Staub, 2015 for a review). For example, garden path sentences (grammatical sentences which lead the reader to predict an alternative syntactic structure, e.g. *the old man the boat*) provoke longer gaze durations and more regressions (Frazier & Rayner, 1982), suggesting that readers predict the simplest syntactic structure and adjust their expectations online as information is accumulated. Word predictability reduces fixation times (Balota et al., 1985; Frisson et al., 2005; McDonald

& Shillcock, 2003; Rayner & Well, 1996; Rayner et al., 2011; Zola, 1984) and increases the likelihood that a word is skipped (Altarriba et al., 1996; Ehrlich & Rayner, 1981; Frisson et al., 2005; Rayner & Well, 1996; Rayner et al., 2011). This indicates that predictable words are faster to process or processed with less precision, as they can be anticipated from sentence context.

Online sentence processing has also been measured using electroencephalography (EEG). Event-related potentials typically show a negative peak during semantic processing, around 400 ms after a word is presented within a sentence (the N400, see Van Petten & Luka, 2012; DeLong et al., 2014 for a review). Words that are unexpected from sentence context have been shown to delay the N400 response (Kutas & Hillyard, 1980) or increase N400 response amplitude (Kutas & Hillyard, 1983; Kutas & Hillyard, 1984; Federmeier & Kutas, 1999; Federmeier et al., 2007; Frank et al., 2015; Kutas & Hillyard, 1984). This indicates that, during sentence reading, words that conflict with readers' expectations evoke a processing cost. Further ERP studies have shown that predictability effects leak into words that have overlapping properties with the expected candidate. The amplitude of the N400 response has been observed to be lower for unexpected words that are semantically related to the predicted word (*she cut her steak with the spoon*) compared with unpredictable words that are unrelated to the predicted target (*she cut her steak with the cup;* Federmeier & Kutas, 1999). Similar effects have been observed for orthographic neighbours of predicted targets (Lazslo & Federmeier, 2009). These findings demonstrate that readers recover and adjust their expectations accordingly. Therefore, the processes that shape word recognition may not only be shaped by preceding context, they may also be revised in the event of conflicting information. Individual words cannot be considered as independent units with self-contained processes, and context effects make it difficult to pinpoint when recognition of a particular word begins and ends.

1.1.6 Summary

The purpose of this section was to highlight that reading is the product of a highly complex set of interacting cognitive processes. Within a fraction of a second, readers identify multiple letters, establish their relative order within a string, parse the string for sub-lexical structures and identify the word within the context of a sentence. Readers demonstrate a high aptitude for executing all of these processes and integrating information accordingly. Further, the weighting of various cues appears to be dynamic based on properties of the word itself, related words and the context that the word appears in. The recurrent focus across this thesis is to consider how different hierarchical processes interact during word recognition. In the following section, I outline various theoretical frameworks which seek to explain how the processes underpinning visual word recognition are integrated.

1.2 Cognitive models of reading

Developments within computational modelling have enabled researchers to develop precise testable models, which simulate word reading behaviour and enable researchers to deduce how well an underlying theory can account for what is observed in practice. When models align with human behaviour, we can draw conclusions about how various orthographic processes are integrated. Reading models can be broadly divided into two classes: models of visual word recognition, which describe the sub-lexical processes that underpin recognition of a single word, and models of sentence reading, which aim to explain how words are read in context.

1.2.1 Visual word recognition

Models of single word recognition tend to focus on how readers use orthographic and lexical knowledge to extract information from the visual input and form meaningful linguistic representations. Below, I outline the most prominent models of single word reading, which include interactive activation models, connectionist models and Bayesian approaches.

1.2.1.1 Interactive activation models

Interactive activation models propose that bottom-up visual information interacts with lexical knowledge (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982). Letter features, letters and words are represented as nodes in a network, which interact with each other using excitatory and inhibitory connections. Letter detectors are activated through bottom-up input from the feature detectors, and the perceptibility of individual letters increases through feedback from top-down word representations. Word nodes send excitatory feedback to letter nodes that correspond with letters that are present in the word, and inhibitory feedback to letter nodes that are not present in the word. This enhanced activation increases the perceptual salience of letters occurring within words, thus interactive activation models can account for the word superiority effect.

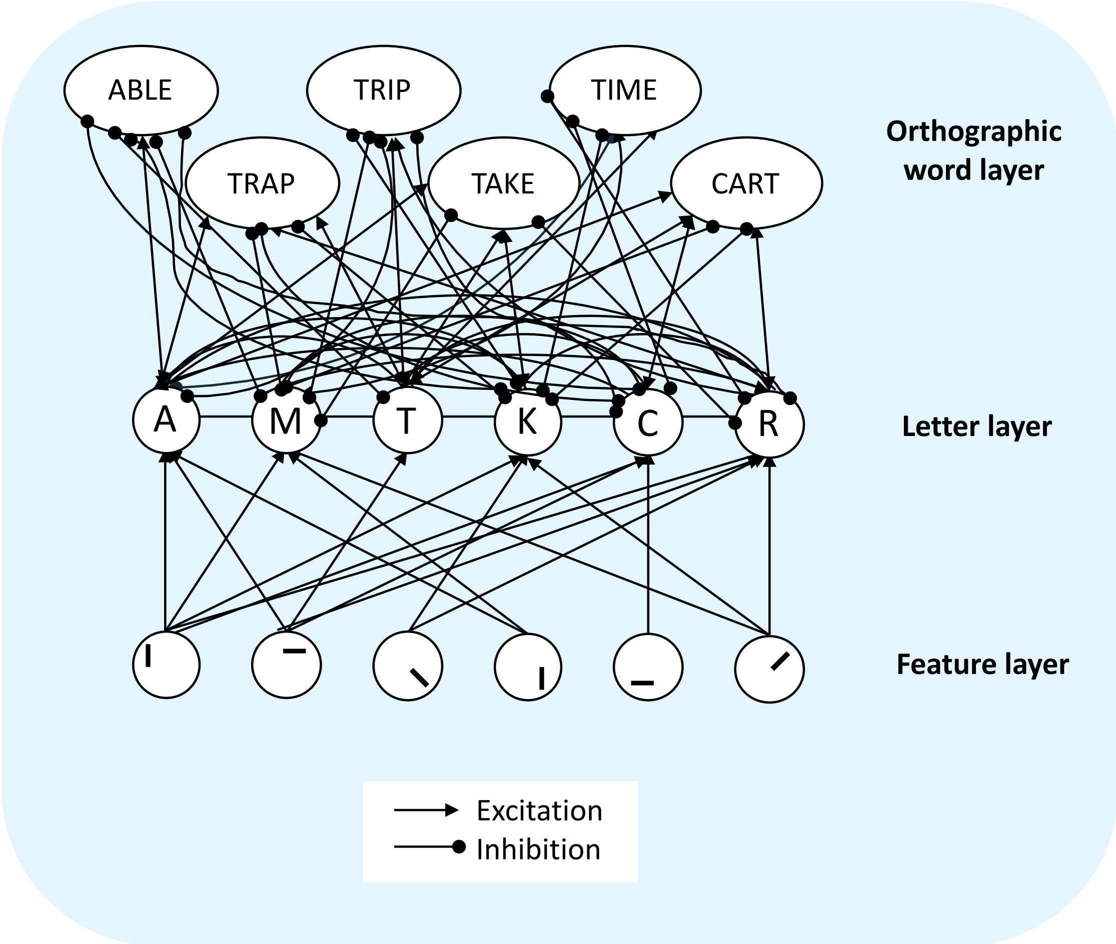

Figure 1. The original interactive activation model, after McClelland & Rumelhart (1981).

The multiple read-out model (MROM; Grainger & Jacobs, 1996) is a based on the interactive activation model, but incorporates the premise that words generate multiple codes during word recognition. Grainger and Jacobs (1996) suggest that readers make responses in experimental tasks (such as lexical decision) when at least one relevant code reaches a critical activation level. The M criterion is based on the activation of individual lexical units surpassing a fixed threshold, which enables readers to identify a specific word. Alternatively, the Σ criterion is based on the summed activation of all lexical units in the orthographic lexicon. Readers may be able to make a lexical decision based on the Σ criterion prior to recognising a specific word under the M criterion, as sufficient overall lexical activity will indicate that the stimulus is a word. Finally, the T criterion is a time-based deadline for negative responses. If M or Σ criteria are not reached before this deadline, the stimulus is classified as a nonword. Critically, Σ and T criteria thresholds are adjustable based on stimuli properties and task demands. For example, the Σ criterion threshold may be raised if nonword stimuli are very word-like, to prevent overall lexical activity from prompting erroneous classification as a word. If readers are asked to prioritise accuracy, the T criterion time limit may be extended to reduce the chance of an incorrect "nonword" response. Adjustable thresholds enable the MROM to explain task specific effects, as well as why certain word properties are facilitative in some cases but not others. For example, why high neighbourhood density benefits word recognition (higher summed lexical activation meets the Σ criterion), unless the neighbours are higher in frequency (high frequency competitors have a lower M criterion) (Grainger, 1990; Grainger & Segui, 1990).

Later models have extended the interactive activation model to propose how orthographic information can be used to produce word pronunciations and meanings. The dual-route cascaded model is a generalisation of the interactive activation model (DRC, Coltheart et al., 2001), which features two separate routes for word reading: a lexical route and a sub-lexical route. Initially, readers establish constituent letters from feature information and identify them within a position-specific slot-based coding scheme. The lexical route implements the framework of the interactive activation model. The orthographic input activates the corresponding whole-word representation within the lexicon. Within the sub-lexical route, the orthographic input is parsed into graphemes, which are individually converted to phonemes based on regular grapheme-phoneme correspondence rules. Words are recognised via both routes in parallel, although recognition via the lexical route is quicker. The lexical route enables readers to correctly pronounce words with irregular grapheme-phoneme correspondences, whereas the sub-lexical route enables readers to read aloud unfamiliar strings when they do not have an existing lexical entry.

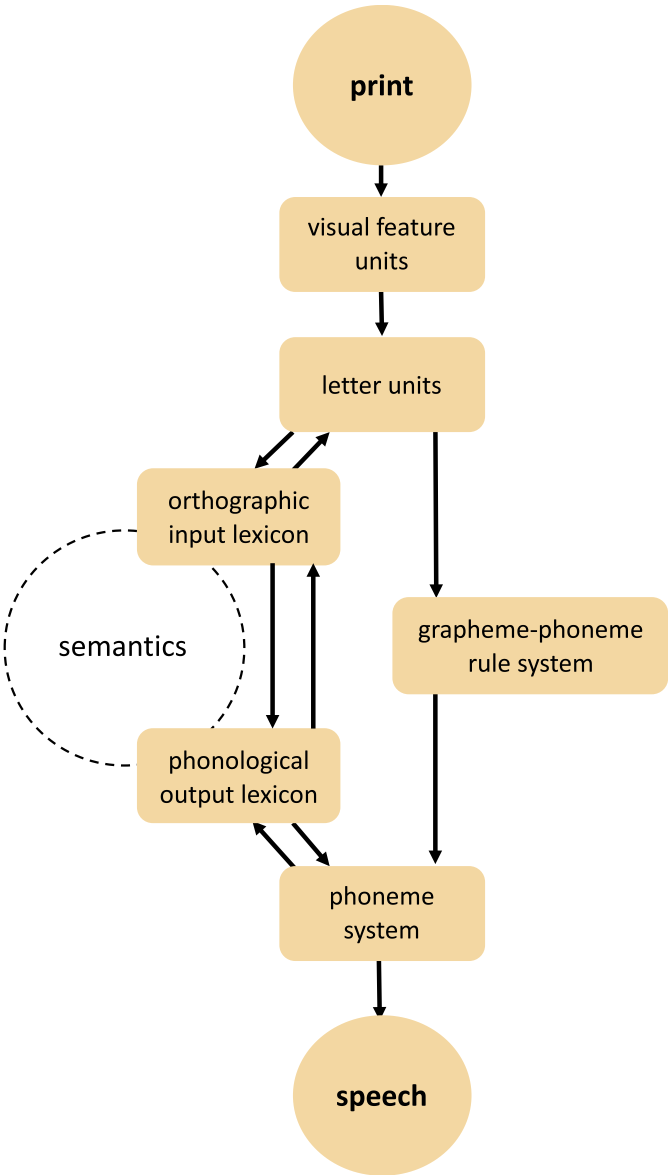

Figure 2. The dual-route cascaded model of reading, after Coltheart et al. (2001). Note: the semantic system has been proposed but not yet implemented within the model.

1.2.1.2 Connectionist models

Interactive activation models represent linguistic knowledge as rules and representations as discrete localised units. Readers are proposed to have specific representations for individual letters or words. In contrast, connectionist models adopt a distributed approach, whereby linguistic knowledge is characterised by shared patterns of activation across units. There are two prominent connectionist models of word reading: the triangle model (Harm & Seidenberg, 2004; Plaut et al., 1996; Seidenberg & McClelland, 1989) and the connectionist dual-process model (CDP+ model; Perry et al., 2007; Perry et al., 2010; Perry et al., 2013).

The triangle model does not feature specific rules on how readers decode words to access their pronunciations or meanings (Harm & Seidenberg, 2004; Plaut et al., 1996; Seidenberg & McClelland, 1989). Words are not represented by local discrete units in the triangle model. Instead, readers recognise words through distributed associations between orthography, phonology and semantics and the weighted connections between them. Unlike alternative models of word reading, the triangle model incorporates learning. Weights between units are adjusted based on repeated activation and error feedback to reflect statistical regularities within the writing system. This provides an advantage as the model has the capacity to adapt the weighting given to various cues based on their salience within the writing system.

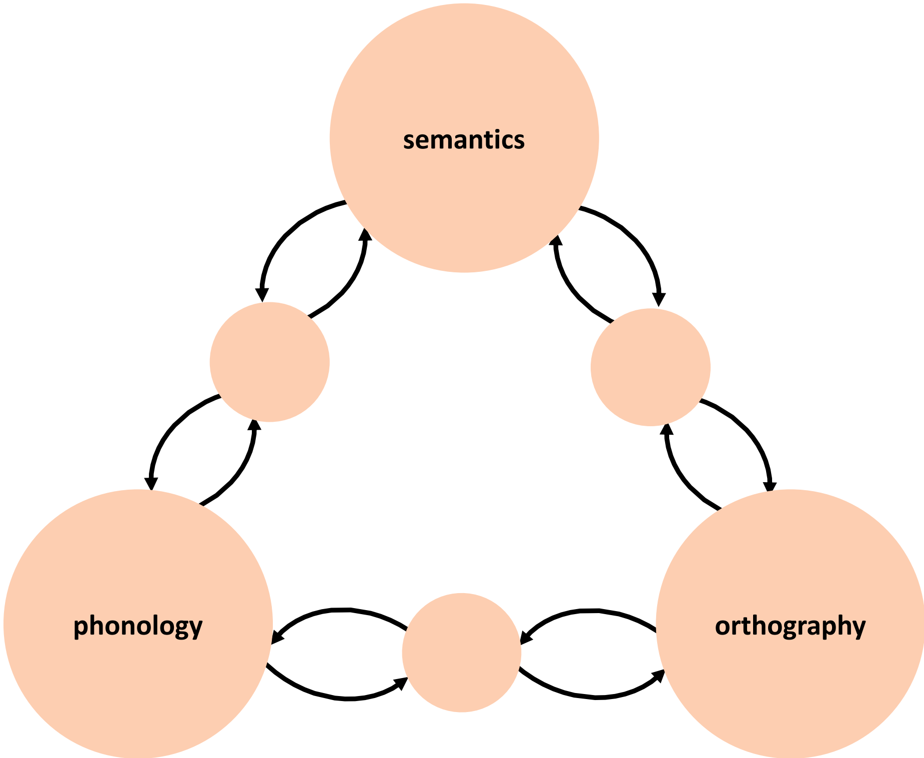

Figure 3. The triangle model, after Harm and Seidenberg (2004).

The CDP+ model (Perry et al., 2007), and its successor (CDP++; Perry et al., 2010; Perry et al., 2013) incorporate the dual-route structure of the DRC model within a connectionist framework. As with the DRC model, CDP+ and CDP++ models include a lexical route and a sub-lexical route. The lexical route is very similar to that of the DRC model. However, the sub-lexical route in these models includes a connectionist two-layered associative (TLA) network that is capable of learning grapheme-phoneme correspondences from the input. The TLA sub-lexical network includes a graphemic buffer, which enables multiple letters to be encoded as single graphemes (e.g. *ght* = /*t*/). This enables the model to code quasi-irregular grapheme-phoneme correspondences at a sub-lexical level, rather than assuming that an irregularity must be processed within the lexical route. The later CDP++ model was extended to allow disyllabic processing, which included the capacity to learn stress assignment. Therefore, the CDP++

model provides an advantage for learning and parsing sub-lexical phonological constituents during word reading.

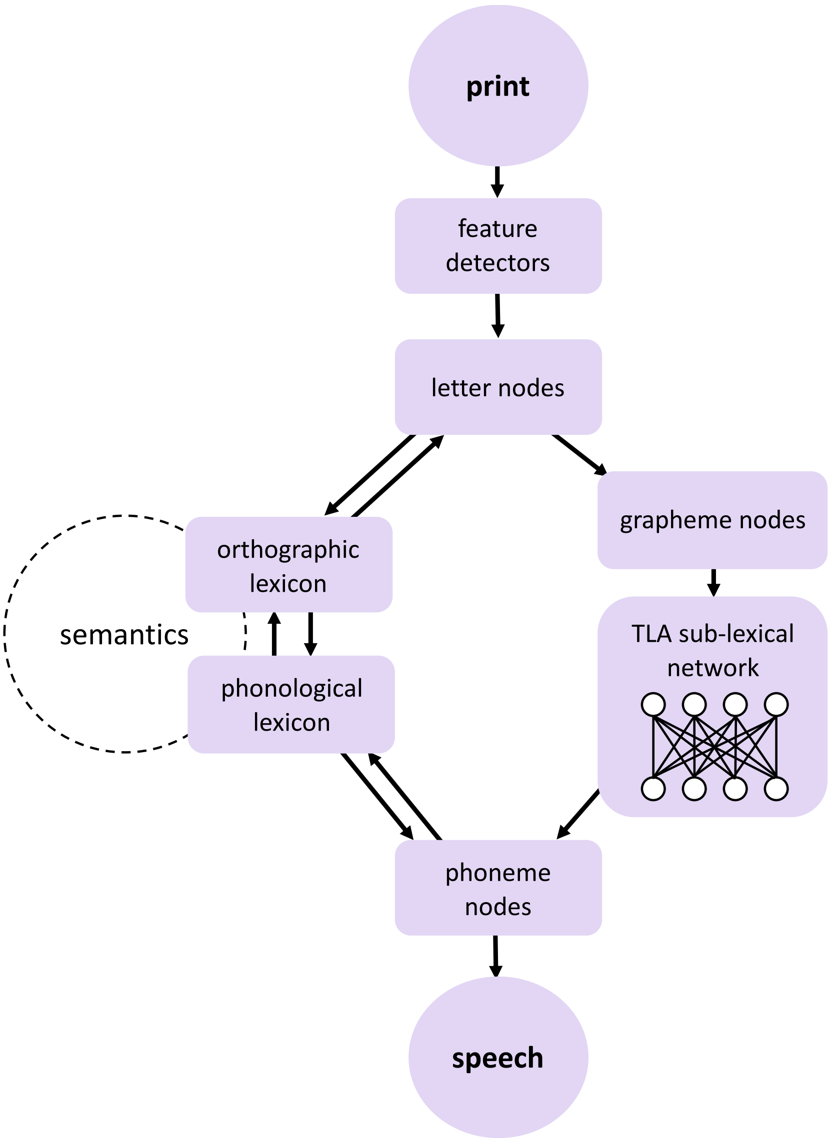

Figure 4. The connectionist dual-process model (CDP+ model) after Perry et al. (2007).

1.2.1.3 Bayesian models

Thus far, the models discussed have outlined hypothetical processes that are specific to reading. Bayesian models take an alternative approach, as they postulate that reading does not require specialised orthographic processing. Instead, Bayesian models propose that reading behaviour is entirely the result of optimal decision-making based on available information. Readers combine tentative evidence with knowledge of prior probability (Norris, 2006; Norris et al., 2010; Norris & Kinoshita, 2012), which is informed by the reader’s understanding of the writing system. Predictions are based on a noisy signal during early processing and refined as information is accumulated over time. Whilst ambiguities in the signal are progressively resolved, readers prioritise information based on which known word best matches the signal, and the likelihood of that word occurring. The prior probability of a particular word occurring can be influenced by properties of the word itself (e.g. frequency) or extraneous contextual factors such as syntactic knowledge, sentence-level semantic interpretation and parafoveal preview (Rayner, 1998). By incorporating contextual cues, Bayesian models take a dynamic approach as they assume that processes may vary across each instance of word recognition.

1.2.2 Models of sentence reading

The majority of sentence reading models are based upon eye-movements. These models can be placed on a continuum based on the extent to which eye-movements are guided by language processing (Reichle et al., 2003). Oculomotor models predict eye-movements based on biological properties of the visual system, whereas processing models posit that eye movements are guided jointly by a combination of linguistic, cognitive and oculomotor factors.

For relevance, this introduction focuses on word recognition within sentence reading models that are driven by cognitive or linguistic behaviour.

One of the most contentious debates in the sentence processing literature is whether words are recognised one at a time in a serial manner, or whether multiple words can be recognised in parallel (see Snell & Grainger, 2019). There is evidence for parallel processing as readers demonstrate flexibility in sentence word order (Mirault et al., 2018). However, the plausibility of parallel processing has been questioned due to constraints on the visual system and attentional distribution (Reichle et al., 2009). Incorporating parallel processing raises additional considerations for how words are recognised in context, such as how readers represent word position and how sub-lexical processes remain co-ordinated with the appropriate word, in order to prevent erroneous leakage across word boundaries. Below, I discuss the leading serial and parallel models of sentence reading and consider their capacity to explain different sentence reading behaviours.

1.2.2.1 E-Z Reader

The E-Z Reader outlines word identification as the "driving engine" of sentence reading (Reichle et al., 2003, p.450), as successful word recognition acts as a signal to move the eyes. Attention is allocated to one word at a time in a serial manner using an attentional spotlight, and each word is recognised across two stages of lexical access. According to the E-Z Reader, words are initially recognised in their orthographic form at the first stage (L_1), and accompanying semantic and phonological information is encoded during the second stage (L_2). Completion of L_1 prompts L_2 processing and plans for the next saccade. Completion of L_2 prompts the oculomotor system to move the attentional spotlight to the next word. The time required for L_1 is dependent on the word's frequency and its cloze probability from sentence context. The extent to which the word can be predicted from context reduces the time required for L_2. If the word can be predicted with complete certainty then semantic and phonological information is already activated during L_1 based on corroborating input from the orthographic form. In this situation, L_2 can be skipped entirely. The E-Z Reader is able to account for a wide range of eye-movements, including fixation times based on word frequency and skipping behaviour based on word predictability (Reichle et al., 2003). However, the serial nature of the model has led researchers to question its ability to account for recent insights into readers' flexibility in word position coding, as shown by the transposed-word effect (*you that read wrong*; Snell & Grainger, 2019).

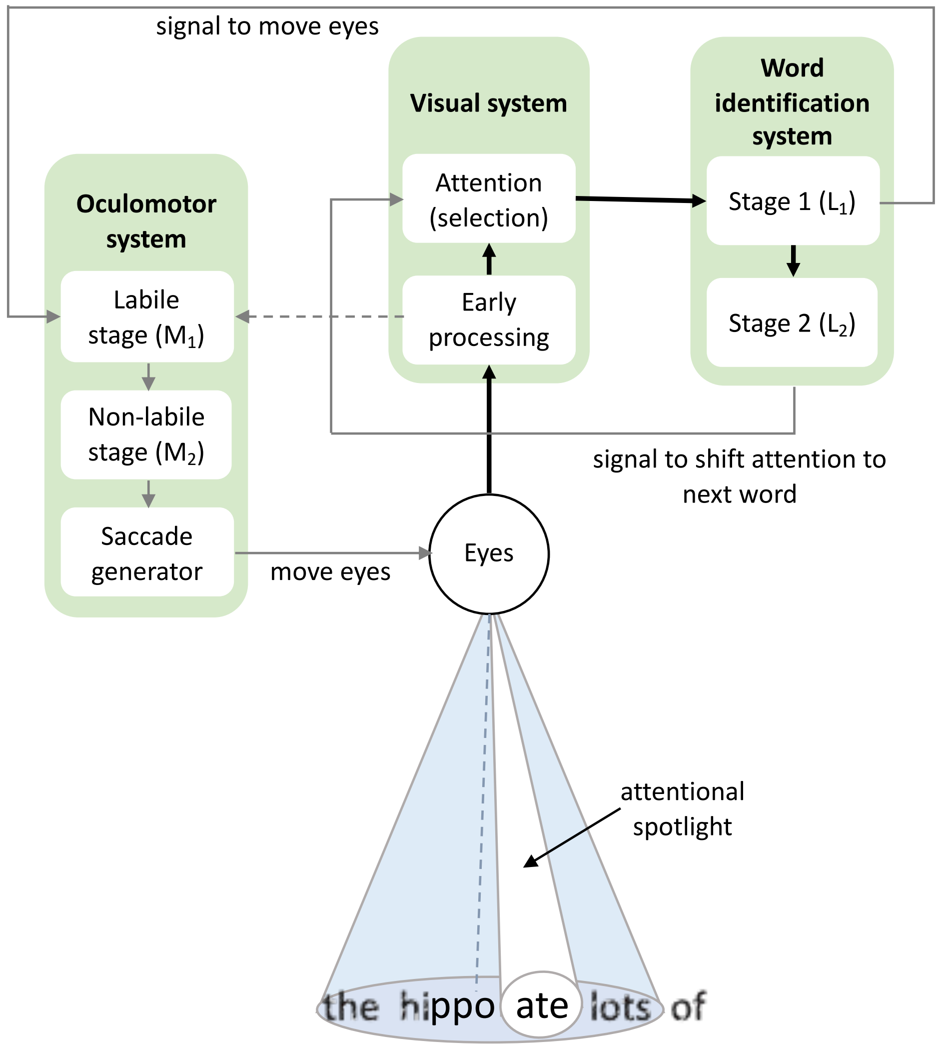

Figure 5. The E-Z Reader model, after Reichle et al. (2003).

1.2.2.2 SWIFT model

The Saccade-Generation With Inhibition by Foveal Targets (SWIFT) model is a parallel processing alternative to the E-Z Reader that also features two stages of word identification (Engbert et al., 2002; Engbert et al., 2005). During the first stage, the lexical activity of a word increases until it reaches a threshold, which is specified by the word's frequency and predictability from sentence context. During the second stage, the word's activation decreases to zero. Thresholds are lower for frequent or predictable words; hence activation takes less time to reach the threshold in the first stage and less time to fall to zero in the second stage. There are two critical differences between the SWIFT model and the E-Z Reader. Firstly, the SWIFT model proposes that words are processed in parallel across a four-word attentional gradient rather than in a serial manner. Within the four-word gradient, attention is directed at words that have received intermediate amounts of lexical processing. Less attention is directed to highly predictable words within the gradient, as activation levels for predictable words are likely to be higher to threshold. This results in a higher skipping probability for highly predictable words. Secondly, the SWIFT model predicts that eye-movements are based on time intervals, rather than successful word recognition. However, this interval may be extended if the reader experiences difficulty identifying a word.

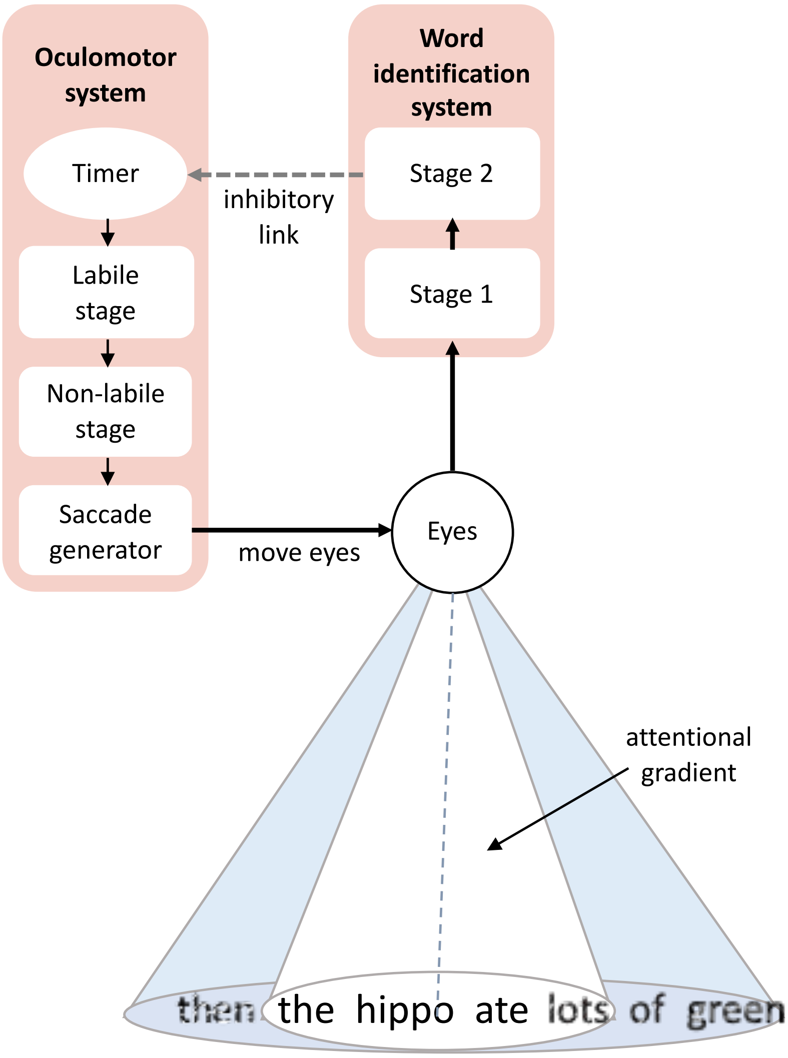

Figure 6. The SWIFT model, after Engbert et al. (2002).

The SWIFT model exhibits similar performance for simulating human behaviour as the E-Z Reader (Reichle et al., 2003), and its parallel-processing framework can also explain flexibility in word order perception (Snell & Grainger, 2019). Like the E-Z Reader, the SWIFT model does not specify the sub-lexical or letter-level processes required for word recognition itself. Integrating within-word processes presents additional complications for parallel processing, as without specifying these lower-level processes, the model cannot explain how readers recognise words simultaneously and maintain separate orthographic processing for within word units. Without these constraints, there is a risk of an extremely noisy output that does not correspond to any word present (Reichle et al., 2003).

1.2.2.3 OB1-Reader model

The OB1-Reader model also incorporates parallel word processing within an attentional window, known as an attentional gradient (Snell et al., 2018). Where the attentional window of the SWIFT model is consistently fixed to four words, the attentional gradient of the OB1-Reader model adapts in size. The attentional gradient widens (enabling greater parallel processing) following each fixation resulting in successful word recognition, and narrows (enabling more focused processing) when readers encounter word recognition difficulty.

The majority of sentence models depict words as the smallest units of representation, and do not consider the letter-level processes required to recognise the words themselves (Snell et al., 2018). Subsequently, there is a notable disconnect between models of single word and sentence reading. However, the OB1-Reader model is an exception, as it is one of the few sentence reading models that considers sub-lexical processing. Readers code open bigrams from letters that appear within the same word. Bigrams do not cross word-boundaries, although bigrams are activated for multiple words simultaneously. Bigrams then activate corresponding word representations and inhibit competitors containing similar letters, as outlined by the interactive activation framework. Activation for viable word representations is also modulated by cloze probability, which is generated by expectations from words that have already been recognised. When word activation surpasses a recognition threshold, words are mapped onto a plausible location within the sentence. According to the OB1-Reader model, readers generate a spatial sentence-level representation in which unrecognised words are represented as “blobs”.

Hence, readers can also use information about word length and syntactic rules to assign words to the correct sentence location, which completes word recognition. Saccade planning (when to move the eyes) is determined by successful word recognition, similar to the E-Z Reader. Saccades are cancelled if a word target to the left of fixation has not been successfully identified. In this case, fixation regresses to the unrecognised target and the attentional gradient is narrowed.

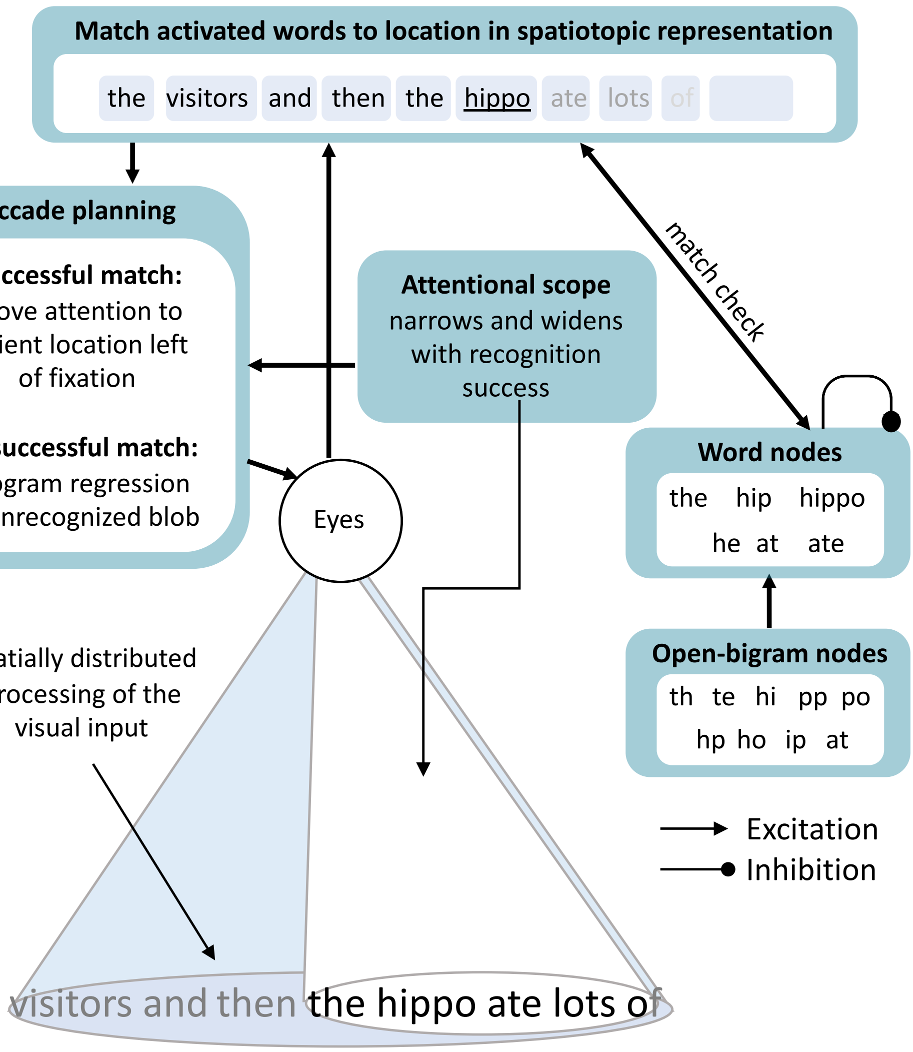

Figure 7. The OB1-Reader model, after Snell et al. (2018).

In theory, the OB1-Reader model is able to account for the broadest range of behavioural effects. It is one of the few sentence reading models to include sub-lexical processing, providing a more comprehensive overview. Parallel-processing assumptions are able to account for transposed-word effects, and the mapping of words to spatial sentence level representations provides a viable prevention of sub-lexical processes leaking across words. However, the model has received some scepticism for the demands that such processes would place on the reader's perceptual span (Reichle & Schotter, 2020). The model implements the interactive activation word recognition network, which relies upon inhibition between word nodes. It is not clear how the interactive activation lexicon could handle activation and inhibition for multiple words simultaneously. Other researchers have suggested the possibility of a blended approach, whereby the early orthographic processing of words is parallel but that lexical access is serial (White et al., 2020). This is supported by evidence of a serial bottleneck, whereby readers can make judgements on orthographic features of multiple words simultaneously, but performance for accurately identifying lexical features (e.g. lexical decision, semantic judgements) suffers when attention is distributed across multiple words (White et al., 2018; White et al., 2020).

1.2.3 Summary

Models of word reading aim to provide a cognitive framework of the processes that contribute to skilled reading. Specific models can either be assessed on technical performance for a particular implementation, or alternatively entire classes of models can be evaluated based on broader in principle theoretical assumptions. Comparisons are not necessarily straightforward, as models vary in their theoretical and computational precision. Further, cognitive models vary in their scope of reading activity (e.g. single word recognition compared with sentence reading). For example, there is often a notable disconnect between models that outline within-word processing and across-word processing. Words are typically considered the largest units of recognition in models that consider sub-lexical processing, whereas words are often smallest units of recognition in sentence reading models. This restricts many models' abilities to account for how sub-lexical information is influenced by surrounding context, an issue which is explored further in Chapter 3.

Whilst computational models provide a logical basis for how processes may be executed, their real-world validity is dependent on what is possible within existing biological structures. The following section summarises what is known about how neural and visual systems engage with and support reading behaviour, with commentary on how these findings align with cognitive models of reading.

1.3 A neuro-biological basis for reading

Reading is a relatively new cultural invention within the history of human evolution; therefore, it is too recent for humans to have specialised neural architecture to support this skill. Instead, there is consensus that the cognitive processes required for reading exploit neural circuitry that has evolved for alternative purposes (the neuronal recycling hypothesis; Dehaene, 2005; Dehaene & Cohen, 2007). Therefore, understanding the constraints of neural and visual systems is an important factor in piecing together the processes that underlie skilled reading.

1.3.1 Reading in the brain

Skilled reading engages multiple regions in the brain, which show different sensitivities to the various processes required for recognising words (see Price, 2012 for a review, and Taylor et al., 2013 for a meta-analysis). These areas are predominantly based in the left hemisphere, and include the angular gyrus, occipitotemporal cortex, as well as inferior, middle and superior temporal gyri. Combined, the neural regions engaged during reading can be described as a reading network. Activity across this network suggests that words undergo multiple levels of neural representation during recognition, as words show similar patterns of activation to each other in different regions based on their visual, orthographic, phonological and semantic properties (Fischer-Baum et al., 2017).

Regions within a proposed neural reading network overlap with two distinct visual pathways that originate from the primary visual cortex: the dorsal and ventral stream (Goodale & Milner, 1992). The dorsal stream, which progresses upwards through the occipito-temporal cortex to the parietal lobe, has been associated with processing phonological information. The dorsal stream typically shows higher levels of activation for alphabetic writing systems (which are based on spelling-sound mappings) relative to logographic writing systems (Bolger et al., 2005), and for pseudowords compared to words (Taylor et al., 2013). This is typically taken as evidence that the dorsal pathway is sensitive to phonological information, as pseudowords can be read aloud using spelling-sound mappings, but do not have a semantic association or an existing entry within the lexicon to allow phonological access via the recognised wordform. The ventral stream extends downwards through the occipito-temporal cortex towards the temporal cortex. Research had shown that ventral stream orthographic processing is lexical in nature and enables print-to-meaning mappings. The ventral stream becomes progressively tuned to word-likeness, as posterior-to-anterior activation becomes hierarchically selective for letters compared to false fonts, pseudowords with legal bigrams compared to consonant clusters, low frequency words compared to pseudowords, and high frequency words compared to low frequency words (Vinckier et al., 2007). The ventral stream overlaps with a region in the left ventral temporal cortex known as the visual word form area (Cohen et al., 2000; Cohen & Dehaene, 2004), which produces greater activation for words compared to pseudowords (Glezer et al., 2009; Schurz et al., 2010), mediated by word frequency (Graves et al., 2010).

Reading engages additional regions that are associated with other forms of linguistic processing. For example, the left middle and superior temporal gyri demonstrate reliable activation during semantic processing (see Taylor et al., 2013). These regions elicit increased activation for meaningful stimuli such as words compared to pseudowords (Binder et al., 2009) and grammatical sentences relative to random lists of words (Bavelier et al., 1997; Humphries et al., 2006, Vandenberghe et al., 2002; Xu et al., 2005). Notably, these regions respond to semantic information across both spoken and written language tasks (Price, 2012), which suggests that semantic processing localised to this region is abstract and modality-general. Researchers have also established regions that are engaged in phonological processing across speech and text. The left inferior frontal gyrus shows increased activation during phonological reading tasks relative to semantic reading tasks, such as rhyme-judgements compared to semantic judgements (Poldrack et al., 1999) or in word-naming for phonologically related words relative to semantically related words (*shin-ship* vs. *shin-leg*, Mechelli et al., 2007). Increased activation is also observed in this area for auditory tasks involving speech, such as phoneme categorisation (Raizada & Poldrack, 2007) or determining syllable order (Moser et al., 2009).

In summary, neuro-imaging evidence has built an extensive map of regions associated with visual word recognition, which indicates that readers establish neural pathways for reading by utilising existing brain circuitry of visual and wider language systems.

1.3.1.1 Neural models of reading

Corroboration across neuroscience and computational models can validate cognitive theories and provide clarification on the brain mechanisms that underpin skilled reading, which can in turn assist in future model developments. However, it can be difficult to integrate neural evidence and cognitive accounts of reading, as cognitive models are not intended to directly simulate neural behaviour (Taylor et al. 2013). A meta-analysis by Taylor et al. (2013) developed a framework in which the authors formulated predictions on how dominant cognitive models of reading aloud would manifest in neural activity. They proposed that individual model components would be represented by a corresponding brain region, and neural activity would be determined by stimulus engagement and processing difficulty. The neural data demonstrated substantial convergence with the functional organisation of DRC, CDP+ and triangle models, as distributions of activity aligned with the prediction that there are multiple routes to word recognition via spelling-sound mappings and/or lexical-semantic correspondences.

Alternative accounts of reading are directly based on the properties of neural pathways. The local combination detector model (Dehaene et al., 2005) proposes that the ventral stream becomes progressively attuned to word recognition as reading proficiency increases, which culminates in a functionally specialised pathway for recognising visual word forms. Words are recognised via a hierarchical network, in which readers encode increasingly large fragments of orthographic information that advance in linguistic complexity. These fragments range from oriented bars (letter features) to case-specific letter shapes, which are subsequently transformed into case-invariant abstract letter detectors. From there, letters are combined into local bigrams and compiled into small words or recurring substrings (such as morphemes). The model is based on neurophysiological models of visual object recognition, with each processing stage based on the size and capabilities of receptive fields within the primate visual system.

Subsequent fMRI studies have provided converging fMRI evidence for the local combination detector account. Vinckier et al. (2007) observed increasingly word-like processing along a posterior-to-anterior gradient within the ventral stream, as regions demonstrated increasing sensitivity to linguistic information within the writing system, such as orthographic symbols (letters vs. false fonts), word-likeness (consonant strings vs. high frequency bigrams) and word frequency. Rothlein & Rapp (2014) localised regions that were sensitive to distinct letter properties such as visual-spatial similarity (*b-h*) or motoric representations based on articulation (*c-g*). Critically, they were able to isolate neural representations based on abstract letter identity, regardless of visual overlap (*A-a*), which supported the existence of neural representations for case-invariant letter detectors. At word level, Taylor et al. (2019) also found that posterior-to-anterior ventral stream activation was initially sensitive to low-level visual information, and then further forward demonstrated neural sensitivities to word information that was increasingly more abstract from the visual form. They characterised areas within the ventral stream that show similar patterns of neural activation based on visual similarities, position-specific shared letter similarities, and position-flexible shared letter similarities of words (based on spatial and open-bigram coding schemes).

A potential limitation of the local combination detector model is that it assumes a one-way feed-forward approach, which restricts its ability to explain how lexical knowledge interacts with sub-lexical processing. This has been challenged by a recent intra-cranial electrode study by Woolnough et al. (2020), which has suggested that ventral stream processing includes feedforward and feedback activity that may be missed by the low temporal resolution of fMRI. Woolnough et al. (2020) identified two spatiotemporally distinct regions that were sensitive to lexical status, but at different time points. Posterior ventral stream regions were first active earlier than anterior ventral stream regions, but also showed lexical sensitivity later than anterior regions. Differences in early and late selectivity could reflect an interaction of bottom-up and top-down processing, as word-likeness recognised in the middle temporal gyrus may propagate backwards and interact with sub-lexical processing in the posterior ventral stream regions. These findings are more cohesive with interactive cognitive models of reading, such as the interactive activation model (McClelland & Rumelhart, 1981) or the dual-route cascaded model (Coltheart et al., 2001), which incorporate feedback from word knowledge into sub-lexical processing. Thus, this theory provides an interactive alternative to the local combination detector model proposed by Dehaene et al. (2005).

1.3.2 The visual system

Reading requires the integration of visual and linguistic information (Grainger, 2018). Therefore, when considering biological constraints on reading, we must also consider how oculomotor processes carry out this task. This can provide insights into how visual information is assimilated and reveal practical limitations for cognitive theories of reading. These processes have been investigated across multiple domains, including psychophysics (e.g. letter feature processing work: Pelli et al., 2006; Pelli et al., 2009) and eye-tracking (see Schotter & Rayner, 2015 for a review), although as Grainger (2018) asserts, there has been little cross-communication between these fields.

CHAPTER 1: INTRODUCTION

One of the key challenges is establishing the boundaries between low-level visual processing and higher-level linguistic processing. In reality, this is more likely to be a graded scale as opposed to a concrete dichotomy. One way in which visual processing can be distinguished from linguistic processing during reading is to compare performance across tasks with varying linguistic demands, or across populations with varying linguistic capacity. For example, trained baboons can fairly accurately distinguish real words from similar letter combinations (Grainger et al., 2012), and human readers demonstrate similar statistical sensitivity effects for linguistic stimuli and non-linguistic visual stimuli with similar complexity (Vidal et al., 2021). Both findings indicate that orthographic processing does not necessarily require pre-existing linguistic representations, which suggests that some aspects of reading can be executed by domain-general visual processes (Davis, 2021). Grainger (2018) has proposed that there is a mid-level vision stage of orthographic processing, in which mechanisms for visual object identification interact with linguistic processing in order to facilitate visual word recognition. In this section, I outline some of the visual factors that may contribute to this integration.

The visual system places various constraints on reading, including visual acuity and crowding (Grainger et al., 2016). Visual acuity refers to the ability to discern fine optical details, which varies across the visual field. Accordingly, readers cannot process all visible information with equal precision. A fixated word is inspected within the fovea, the highest point of acuity within the visual field (Drieghe, 2011). Acuity then declines as distance from the fovea increases (Oyster, 1999). Retinal information just outside the fovea (parafoveal preview) also plays an important role in skilled reading, as evidence suggests that readers can extract broader information about word length and form within this region (Grainger et al., 2016; McConkie & Rayner, 1975). Information about upcoming words may reduce the time required for subsequent fixation, or enable them to be skipped altogether (Drieghe et al., 2005). Crowding is an alternative perceptual effect whereby peripheral objects might not be distinguished from each other if they appear too close together (Whitney & Levi, 2011). This has implications for processes such as letter identification, as letters typically appear clustered together. Crowding places additional constraints on the span of letter-level processing within the visual field. Readers are less accurate at identifying peripherally presented letters surrounded by additional flanking letters compared to peripherally presented letters in isolation (*ara* vs. *r* ; Legge et al., 2007), and less accurate at identifying peripheral letters with narrow inter-letter spacing (Liu & Arditi, 2001).

The visual system also adapts based on reading experience. For example, skilled readers are more tolerant of crowding in letters compared to symbols, shown in a two-alternative forced choice identification task (Grainger et al., 2010). Based on this evidence, Grainger et al. (2016) proposed that readers refine their receptive field size during letter identification to reduce inter-letter interference. Further evidence is found in differences in neural responses between literate and illiterate adults (see Dehaene et al., 2015 for a review). Literacy increases fMRI responses associated with retinotopic mapping in early visual areas (V1) for horizontally aligned stimuli (Dehaene et al., 2010). The bias for horizontally aligned stimuli suggests that readers apply these processes to strings that are word-like. Notably, this increase in neural activity is not exclusive to letters, which has led Grainger et al. (2016) to suggest that reading experience increases broader proficiency in parallel mapping of visual features onto location-specific shapes.

1.3.2.1 Visual models of reading

Grainger et al. (2016) proposed an alternative cognitive model of reading that integrates properties of the visual system. Letters are most visible when they are at the centre of fixation (maximum acuity) or are flanked by blank spaces (minimal crowding), resulting in a W-shape of visibility (see Scaltritti et al., 2021 for experimental evidence). Readers then establish orthographic features and chunks using coarse and fine-grained codes, based on the dual-pathway model of Grainger and Ziegler (2011). Coarse codes generate whole-word orthographic forms and enable faster access to semantics, whereas fine codes generate phonological codes with greater precision. Coarse orthographic features are represented as bigrams (*shard: sh, sa, sr, sd, ha, hr, hd, ar, ad, rd.)*, which provide letter-position information while allowing position flexibility. Fine orthographic chunks are represented as graphemes (*shard: sh-ar-d)* or other frequently co-occurring letters (such as morphemes) to assist spelling-sound mapping and enable processing of sub-lexical units. Words in a sentence are processed in parallel, with intermittent levels of precision based on their position within the visual field. Fixation brings a word into the fovea, where the increase in visual acuity enables readers to extract fine and coarse orthographic information. Words outside of the fovea appear blurred due to lower visual acuity; therefore, the ensuing word is partially processed via coarse code. Acuity is further limited for words within peripheral vision, although readers can extract broad information about word length to guide eye movements and narrow potential upcoming word candidates.

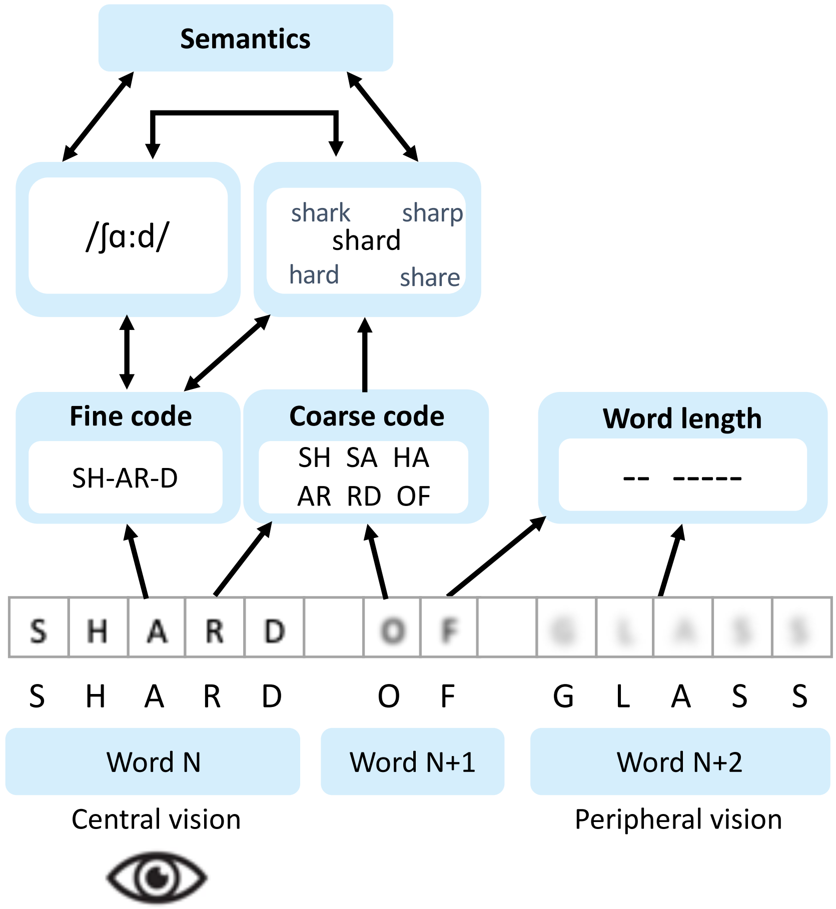

Figure 8. A visual model of reading, after Grainger et al. (2016).

1.3.3 Summary

This section has summarised how the cognitive processes that underlie skilled reading may be executed within existing neuro-biological architecture. An extensive body of evidence from both neuro-imaging and eye-tracking has provided a rich account of biological constraints on reading, as well as how neural and visual processing adapts to support this skill. The final part of this introduction considers how word recognition processes may be shaped by properties of the writing system. I outline the critical role of the text environment in influencing orthographic processing, and highlight that appreciating the characteristics of the writing system as an input is essential for understanding the processes that support visual word recognition.

1.4 How is reading shaped by properties of the writing system?

Due to the learned nature of reading, exposure to the writing system leads to fine-tuning of reading processes. As discussed previously, reading behaviour is influenced by the statistics of natural language. For example, word frequency effects are a prime example of how the salience of word-level information is based on prevalence of a stimulus within the print environment. Critically, there is also evidence that reading is shaped by characteristics of the writing system itself. Skilled readers encounter hundreds of millions of words and billions of letters over their lifetime (Pelli et al., 2006), which plays a critical role in refining orthographic knowledge of how the writing system represents language as visual symbols. For example, readers adjust prioritisation of different visual features as they gain expertise in an unfamiliar alphabet, in order to best discriminate between letters (Wiley et al., 2016). This section outlines the critical role of the writing system as the input for learning, and how characteristics of the text environment influence how orthographic information is extracted.

1.4.1 Distributional salience

Statistical learning (the ability to acquire knowledge about patterns in the environment) has been established as an important tool for implicit language learning. This has received extensive focus in spoken language (see Romberg & Saffran, 2010 for a review), and substantial evidence also suggests that readers also demonstrate statistical sensitives in the written language environment. Developmental research has shown that children quickly develop understanding of letter distributions. For example, in the first year of reading instruction, children gain awareness of common letter doublets (e.g. *ll* but not *ww*; Deacon et al., 2008). By the first grade (6-7 years old), children are more likely to judge pseudowords as more word-like if they conform to letter frequency and co-occurrence statistics of their native language (Cassar & Treiman, 1997; Pacton et al., 2001). These statistics are also reflected in primary school age spelling behaviour (Pollo et al., 2009). Similar statistical patterns emerge when adults are asked to spell pseudowords, as spellings tend to reflect the regularities of letter distribution in the reader's native writing system (see Kessler, 2009 for a review). For example, readers imitate patterns of letter-doubling (Treiman & Boland, 2017) and mimic the most frequent graphemes that reflect phonemes in written words with similar structures (Treiman, 2017).

Recently, Schubert et al. (2020) used machine-leaning to investigate the extent to which readers can learn about different characters in their orthography based on the statistics of the text environment alone. The authors investigated this question by applying the distributional hypothesis, which suggests that we learn about a specific element based on co-occurrences with other elements (Harris, 1954). This hypothesis has been used to explore semantic relationships, based on the premise that words with similar meanings tend to occur in similar contexts (see Boleda, 2020 for a recent review). This is summarised by Firth (1957), "you shall know a word by the company it keeps" (p. 11). In line with this hypothesis, Schubert et al. (2020) investigated the hypothesis that readers can identify a letter based on the company it keeps. After exposure to 12 million words across 44,000+ documents, the neural embedding model *word2vec* (Mikolov et al., 2013) was able to differentiate between letter and non-letter characters (numbers and symbols), upper and lower cases, and consonants and vowels. Whilst these models are not intended as a theory of how humans extract statistical regularities, they do demonstrate the rich contextual orthographic information available from the environment independent of any understanding of semantics or phonology.

Readers also demonstrate increased sensitivity to orthographic units that provide salient linguistic information about the sounds or meanings of words. For example, evidence outlined earlier in this chapter suggests that readers rapidly decompose words into constituent graphemes and morphemes (Rey et al., 2000; Rastle et al., 2004). When discussing morphology, Rastle et al. (2000) propose that readers capitalise on orthographic “islands of regularity” which offer a degree of systematicity in the mapping between printed words and their meanings. This can explain why we observe facilitation in morphological (*farmer-FARM*) and morpho-orthographic (*corner-CORN*) priming, but not in words with equivalent orthographic overlap (*window-WIND*; Rastle et al., 2004). It suggests that orthographic letter strings associated with a morpheme have a special status, as morphemes reflect salient statistical information within the writing system (Rastle, 2019b).

Overall, there is collective evidence to show that the written environment plays a key role in shaping orthographic representations. Distributional salience and statistical regularities within the writing system have a substantial impact on what orthographic information becomes regarded as privileged in order to support optimal word recognition.

1.4.2 Cross-linguistic differences

It is clear that reading behaviour is shaped by properties of the language and its extended writing system. As a result, the way in which reading is shaped by the environment will not be universal across literate populations, as different writing systems will have different kinds of salient characteristics (see Frost, 2012b). Frost (2012b) proposed that “every language gets the writing system that it deserves" (p. 267). In other words, the accompanying writing systems will be structured to best convey idiosyncratic characteristics of their respective languages. One of the ways that writing systems differ is the extent to which the orthography reflects phonological or semantic information. However, given the arbitrary relationship between phonology and semantics in speech, orthographic regularities in one domain are often at some cost to the other (see Frost, 2012b for an overview of five distinct languages). Therefore, it is widely agreed that no language has a completely optimal writing system.

Cross-linguistic comparisons indicate that writing systems evolve to accommodate salient characteristics of the language. English has an alphabetic writing system that features fairly consistent mappings between orthography and phonology, although there are also many irregularities which may be due to preserving other structures, such as morphology (Rastle, 2019a). In comparison, agglutinative languages such as Finnish tend to have high orthographic consistency, as words can be formed by compounding morphemes without changing their spelling or pronunciation. This can result in very long words, which may increase processing demand. However, Frost (2012b) hypothesizes that the consistency between orthography and phonology should reduce this load. Korean Hangul also prioritises transparency between orthographic and phonology. Hangul has a predictable CVC syllabic structure; thus, syllables are represented orthographically as demarcated blocks (e.g. 햇빛, a two-syllable word meaning "sunlight"). Further, consonant characters often illustrate the shape of the vocal organs required to produce the corresponding phoneme (Pae et al., 2019). For example, ㄴ (/n/) symbolises the front of the tongue raised behind the teeth, whereas ㄱ (/k/) represents the back of the tongue raised towards the soft palate. Languages also vary in the phonological information that needs to be conveyed orthographically. For example, Thai is a tonal language, therefore the writing system features diacritic tone markers to differentiate between homophones. Thai also features classifiers, which are characters appended to groups of nouns that are often semantically related (e.g. ลูก denotes a small round object; Hudak, 2016). Therefore, words with shared phonology can potentially be disambiguated by their classifiers.

It is important to note that writing systems do not evolve with the sole purpose of providing phonological information. Instead, Frost (2012b) proposes that writing systems evolve to optimise cues relating to spoken words and their meanings, whilst maintaining minimal orthographic load for ease of processing. This can explain why phonological information is often underspecified within writing systems where it does not play a critical role in disambiguating between words. For example, Semitic languages (such as Hebrew and Arabic) omit the majority of vowel information from print. Frost (2006) attributes this to the well-established internal morphological structure of Semitic words. The word meanings are expressed via tri-consonantal roots, therefore providing minimal orthographic content elevates readers' abilities to efficiently extract the root structure. As internal word structures are highly constrained, accessing the root provides an efficient route for lexical access and unlocking of vowel information (Frost, 2006). Some of the most extreme examples are found in logographic writing systems, in which words or morphemes are denoted with a single character. An example is Chinese, in which most characters first denote a semantic radical followed by a phonetic radical. Semantic information appears to take priority over phonological information in how words are orthographically conveyed. In fact, Frost (2012b) highlights that Chinese dictionary entries are organised by their semantic radicals, with phonological radicals offering secondary phonological information. Notably, Chinese words are predominately mono-morphemic with a strict syllabic structure, which results in a very high prevalence of homophones. Therefore, a 'meaning-first, sound-second' writing system is arguably more suited for optimal word recognition.

CHAPTER 1: INTRODUCTION

As orthographic representations are shaped by the written environment, readers of different writing systems likely attribute greater weighting to different kinds of orthographic information. This has been formally proposed as the orthographic depth hypothesis (Katz & Feldman, 1983; Katz & Frost, 1992) and psycholinguistic grain-size theory (Ziegler & Goswami, 2005; see also Grainger & Ziegler, 2011), which are both based on the assumption that words are recognised via at least two pathways (phonological and orthographic). These accounts propose that readers' reliance on either pathway is weighted by the consistency of orthography to phonology mappings within their language. There is some experimental evidence to support this; readers of languages with high orthographic consistency have routinely shown stronger word length effects (Ellis & Hooper, 2001; Goswami et al., 1998) and faster pseudoword reading latencies (Aro & Wimmer, 2003; Frith et al., 1998; Landerl, 2000; Mann & Wimmer, 2002; Rau et al., 2015; Thorstad, 1991), both of which have been interpreted as greater experience with decoding small-unit grapheme-phoneme correspondences. There is also evidence that readers of languages with high and low orthographic consistency show divergences in reading aloud even when the written input is the identical (Ziegler et al, 2001b), however a recent re-analysis has suggested that more evidence is required after failure to replicate some of the findings (Schmalz et al., 2017).

Cross-linguistic differences are not necessarily contingent on the relationship between orthography and phonology. Letter position coding provides another striking example of cross-linguistic differences in the initial stages of orthographic processing. Readers of many Indo-European languages demonstrate flexibility in letter position coding, as shown by the transposed letter effect (Perea & Carreiras, 2008). However, the transposed letter effect is not observed in other writing systems, such as Hebrew (Velan & Frost, 2007), Arabic (Boudelaa et al., 2019; Perea et al., 2010) and Korean (Lee & Taft, 2009; Lee & Taft, 2011; Rastle et al., 2019). Frost (2012b) proposed that letter position coding may be dependent on orthographic density, defined by the prevalence of anagrams. This theory was computationally tested by Lerner et al. (2014), who found that models were more reliant on positional information in training sets with higher proportions of anagrams. However, it is difficult to test this in natural languages as writing systems have additional differences over and above orthographic density. For example, Hebrew features an embedded morphological structure, and Korean has a strict syllabic structure, both of which would also be disrupted by letter transpositions. This issue is addressed experimentally in Chapter 5.

1.4.3 Summary

The processes that underpin skilled reading are not only shaped by cognitive or neurobiological capacities, but also by properties of the writing system itself. Humans are highly skilled at detecting patterns in their linguistic environment, which plays a major role in learning to read and influencing how orthographic information is optimally weighted long-term. In order to fully understand the representations that arise during reading, it is fundamental to appreciate the nature of the input as a starting point (Rastle, 2019a). As outlined above, the learned nature of reading and the critical role of the writing system prevents skilled reading from being universal experience across languages. Cross-linguistic comparisons across different writing systems can reveal the extent to which specific aspects of visual word recognition are due to general cognitive properties, which should occur across all languages, and the extent to which they are shaped by the environment, where cross-linguistic differences in reading behaviour will occur.

1.5 Thesis overview and aims

Reading is a highly complex learned skill, which is shaped by the constraints of existing cognitive and neuro-biological structures, as well as distributional information from the written environment. The over-arching aim of this thesis is to advance understanding on how skilled readers hierarchically integrate the representations that arise during the early stages visual word recognition. The experimental work investigates both the situational factors that influence how readers weight orthographic information 'in the moment', as well as properties of the writing system that shape long-term representations over years of acquisition.

Chapter 2 outlines some of the methodological considerations that were undertaken whilst conducting this research. Chapters 3 and 4 focus on how representations are formed in the short-term, by considering how the processes that underpin letter identification may be mediated by surrounding orthographic information. Chapters 5 and 6 focus on how readers' sensitivity to various orthographic properties is shaped through long-term learning. Chapter 5 explores whether the flexibility of letter position coding varies based on orthographic density (or number of anagrams) within an artificial writing system. Chapter 6 examines whether readers form specific neural representations for letter combinations that reflect salient statistical information (such as morphemes), using fMRI and representational similarity analysis. Finally, Chapter 7 provides a general discussion of the overall findings, which indicate that word recognition is signal-contingent. Readers adapt how various sources of orthographic information are weighted and integrated during the initial stages of word recognition, based on both salience within the writing system and the immediate context available. Conclusions consider how these findings relate to computational theories of reading and how they are represented in the brain.

CHAPTER TWO: METHODOLOGY

This thesis features four independent studies that investigate the hierarchical representations that arise during the initial stages of word recognition. Each study incorporates different behavioural and neuroscientific methods, which are outlined within the accompanying chapter. Therefore, the current chapter does not serve as a manual for the methods employed, but instead outlines some of the broader conceptual and statistical considerations that arose whilst this work was conducted.

2.1 Differentiating between influences of short-term context and long-term knowledge

The representations that arise during reading can broadly be attributed to long-term knowledge or temporary online representations that manifest in the moment. However, it is important to note that theoretical accounts may dispute the dichotomy of this distinction, and provide alternative theories on how long-term knowledge is stored (e.g. connectionist theories, see Seidenberg, 2005). This section briefly summarises methodological considerations that were undertaken when investigating long-term and short-term representations. Specifically, I outline the approaches taken to answer the following questions:

1) How do readers weight information in the moment? How malleable are the word representations that arise and how are they impacted by temporary situational context?
2) How do readers form weightings over years of acquisition? What information do readers pay attention to and encode in long-term representations during learning?

2.1.1 Representations shaped by short-term situational factors

The studies presented at the beginning of this thesis examine how representations are formed within individual instances of visual word recognition, and investigate the situational cues that influence how orthographic information is processed. These representations are formed as a result of online processing, and provide insight on how various linguistic cues are weighted and integrated in an adaptable manner.

Chapters 3 and 4 investigate how temporary representations are influenced by immediate context. Specifically, we tested whether letter identification accuracy varies based on properties of the letter string and/or surrounding words within a sentence. These experiments implemented a Reicher-Wheeler task (Reicher, 1969; Wheeler, 1970), whereby a participant is briefly presented with a letter string and then asked to decide which of two letters appeared in a specified position within the string. One of the letters is the target letter (which actually appeared within the specified position within the string), whilst the other letter is a foil letter (which did not appear in the string at all). The task is designed so that substitution of the target letter with the foil letter always results in a string with the same orthographic status in order to minimise post-hoc guessing. For example, if the letter string was a word such as *crowd*, the target and foil letters may be *d* and *n* respectively, as either letter would result in a real word (*crown/crowd*). Similarly, if the letter string was a pseudoword such as *crowl,* the target and foil letters may be *l* and *b* as both would form pseudowords (*crowl/crowb*). Reicher-Wheeler tasks reliably demonstrate the word superiority effect, which refers to readers' increased ability to accurately identify letters in words relative to pseudowords (Reicher, 1969; Wheeler, 1970).

The word superiority effect is a prime example of how readers adapt based on the information available. It demonstrates that the representations that support letter identification are not solely contingent on properties of the letters themselves, but also external factors that are likely to change across instances of recognition. In the context of the word superiority effect, it is clear that word-level representations are not critical for letter identification, as readers are able to recognise letters presented in isolation, or in pseudowords that they have not encountered before. However, the word superiority effect shows that word-level information still plays a substantial role during letter identification, as accuracy suffers when a corresponding word representation isn't available. By comparing proficiency of a specific reading task across different situations, we can assess the importance of the various cues supporting these processes.

In the current thesis, we used the word superiority effect as a window onto the representations that are used to support visual word recognition processes when different degrees of context are available. For example, is the strength of the word superiority effect modulated by predictability from sentence context? Is task performance impacted by visual featural similarity of target and foil letters, and does this have a greater/lesser impact when there is a corresponding word level representation? The methodologies for the studies presented in Chapters 3 and 4 were partly inspired by the work of Mattys et al. (2005), which investigated how various linguistic and acoustic cues are integrated during auditory speech perception. In this work, the authors systematically pitted different cues against each other, and measured the impact on speech segmentation (the ability to detect word boundaries during speech). They found that cues were hierarchically weighted, with descending priorities from lexical to acoustic information. Lower level acoustic cues drove segmentations in the absence of lexical information, but became redundant when lexical information was available. Ultimately, the study demonstrated that the word representations that arise from speech are *signal-contingent*. We took the same approach to investigate whether this is also the case for word representations arising from text. This enabled us to develop an account of how readers integrate low-level visual information and high-level sentence information during word recognition, in situations where cues provided either collaborative or conflicting information.

2.1.2 Representations formed from long-term knowledge

In the second half of this thesis, there is a shift in focus from short-term situational representations to long-lasting word representations that are typically established over years of reading experience. Chapters 5 and 6 examine how long-term word representations are shaped by exposure to the writing system, and whether certain aspects of the writing system have greater salience as privileged information. For example, certain cues may exert a greater influence on word recognition if they play a critical role in disambiguating between multiple word representations. Alternatively, long-term representations may be sensitive to information based on distributional salience. This could apply to multiple aspects of the writing system, such as co-occuring letter combinations, or orthographic information that provides systematicity in the links between print and sound or meaning (e.g. morphology).

2.1.2.1 Artificial language learning paradigms

Chapter 5 focuses upon how readers learn to weight specific cues based on the usefulness of their contribution for efficient word recognition. We investigated cross-linguistic differences in letter position coding, after a body of literature indicated that letter position is encoded with greater flexibility in some languages compared to others (Frost, 2012b). We aimed to test the hypothesis proposed by Frost (2012b) that flexibility in position coding emerges in languages where it maximises the efficiency of word recognition. However, testing this hypothesis was not straight-forward as there are substantial challenges with drawing cross-linguistic comparisons. Most prominently, there are multiple substantial differences across languages, which makes it difficult to isolate relevant contributing factors. In addition, there is also likely to be substantial variation across readers of different languages. For instance, different reading populations will vary in the method of reading instruction received, overall reading proficiency and level of reading experience. In light of these differences, it is difficult to draw definitive conclusions about the impact of specific factors on the development of orthographic representations.

We overcame these limitations by using an artificial language learning paradigm to investigate how properties of the writing system influence the precision of letter position coding. This enabled us to create a tightly-controlled reading acquisition environment in which adults were trained to read novel words in unfamiliar scripts over an extended period of time. Our artificial language systems were designed to be identical in all dimensions except for the factor of interest, which in our case was orthographic density (the prevalence of anagrams). We predicted that letter position coding would be less flexible in languages with high orthographic density. This was based on the expectation that readers would have greater sensitivity to precise positional information, as the risk of identifying another word in error would be more likely to outweigh the benefits of position flexibility. This approach not only permitted precise control over properties of the writing system, but also the manner in which readers were taught to read it. We ensured that participants received the same training in either writing system, based on tasks implemented in previous artificial reading acquisition studies (see Taylor et al., 2017).

Previous artificial language learning studies have been highly effective in simulating the acquisition of various types of linguistic information (Bowers et al., 2005, Clay et al., 2007; Ellis & Schmidt, 1998; Fitch & Friederici, 2012; Gaskell & Dumay, 2003; Hirshorn & Fiez, 2014; Rastle et al., 2021; Tamminen, et al., 2015; Taylor et al., 2011; Taylor et al., 2014; Taylor et al., 2017). Studies have provided insights on learning new grammar systems (Batterink & Paller, 2017; Mirkovic & Gaskell, 2016) and pseudo-morphological relationships (Tamminen et al, 2015). Further, completely novel orthographies with unfamiliar symbols have been used to study how readers learn print-to-sound and print-to-meaning mappings (Mei et al., 2013; Taylor et al, 2017; Rastle et al., 2021), and to validate methods of reading instruction (Taylor et al., 2017; Rastle et al., 2021).

One of the benefits of conducting artificial language learning studies with skilled adult readers is that it is highly efficient. Participants often learn quickly and demonstrate high proficiency after a single session. However, there is some scepticism over how well artificial language learning truly reflects naturalistic reading behaviour (see Pothos, 2007). For example, adult readers are already skilled in an existing writing system, which is likely to influence their behaviour when learning a novel orthography. Similarities between the native and artificial language can provide readers with a blueprint that they might not otherwise have, and differences may cause interference. Further, there are questions around the extent to which artificial language learning under laboratory conditions reflects strategic problem-solving rather than naturalistic reading. In order to perform the task well, participants need to achieve proficiency suitable for the short timeframe of the experiment. This may reduce the relevance of artificial languages in understanding the formation of long-term abstract knowledge as the usefulness of this would fall beyond task demands (Taylor et al., 2017). Despite these concerns, there are several factors which provide support that representations that would support long-term knowledge. For example, artificial languages evoke the same behavioural effects as in natural languages, such as frequency and consistency effects (Taylor et al., 2011). Other studies have shown that readers can generalise the rules of the artificial language to pronounce or understand the meanings of untrained items (Rastle et al., 2019; Tamminen et al., 2015; Taylor et al., 2011; Taylor et al., 2014), and that this knowledge is preserved over a long timeframe (Havas et al., 2015; Laine et al., 2014; Merkx et al., 2011; Tamminen & Gaskell, 2008).

Over the past decade, researchers have also combined artificial language learning with neuro-imaging, which have demonstrated similarities in brain activity with naturalistic reading (Mei et al., 2013; Taylor et al., 2017; Taylor et al., 2019). For example, Taylor et al. (2017) scanned adults before and after learning a new orthography, and found that later scans showed ventral stream specialisation during semantic reading tasks, as well as dorsal stream specialisation in phonological reading tasks. Further, Taylor et al. (2017) provided quantitative evidence that the neural activity elicited by reading aloud artificial stimuli was similar to reading aloud English stimuli. Spatial distribution analyses confirmed that activation differences for participants reading trained and untrained items in the artificial orthography were akin to differences in neural activation for reading words versus pseudowords in English.

In summary, artificial languages have been a valuable tool for simulating language learning and understanding the principal mechanisms behind it. This method provides an innovative approach for comparing how long-term representations are shaped in different languages, whilst eliminating confounding factors present in naturalistic comparisons. In the work presented in Chapter 5 capitalises on this approach to simulate a precisely controlled cross-linguistic learning environment, to further understanding on how the environment shapes long-term representations around letter position coding.

2.1.3 The neural basis of representations during reading

Chapter 6 focuses upon whether long-term representations are sensitive to statistically salient information within the writing system, and how this manifests as neural activity in skilled readers. Specific brain regions develop a specialised sensitivity to various kinds of orthographic information (e.g. visual word form area; Cohen et al., 2000; Cohen & Dehaene, 2004), which provide an indication of the long-term representations forged to support visual word recognition. We used magnetic resonance imaging (MRI) and representational similarity analysis to characterise the neural representations that occur during visual word recognition. Specifically, we sought to investigate whether skilled reading evokes neural representations sensitive to morphological information in order to facilitate efficient mapping between print and meaning. This section highlights the general methodological benefits of representational similarity analysis, and how it can play an important role in understanding the neural basis for representations that arise during reading. This can greater inform us on sensitivities to particular aspects of the writing system, and provide insight on the types of information prioritised in long-term memory.

Neuro-imaging methods provide insight into the brain regions engaged during specific reading processes. In recent years, reading researchers have been able to conduct more fine-grained analyses on the neural representations that contribute to reading due to advancements in multivariate pattern analysis techniques (Baeck et al., 2015; Fischer-Baum et al., 2017; Rothlein & Rapp, 2014; Taylor et al., 2019). Representational similarity analysis is a multivariate technique based on the principle that stimuli that share similar representations will elicit similar neural response patterns in the relevant region (Kriegeskorte et al., 2008). Analyses are conducted using the following practical steps. First, researchers strategically select stimuli that can be compared for similarity based on particular cognitive theories or representational properties. Each stimulus is compared to one another in a hypothetical matrix that predicts how similar neural responses should be in regions that are sensitive to the comparison of interest. Hypothetical matrices are often constructed by comparing stimuli which are similar along one dimension but not another. For example, *PARROT-CARROT* would be correlated as similar in a hypothetical matrix expressing orthographic similarity, whereas *PARROT-TOUCAN* would be correlated as dissimilar. In contrast, the reverse would be true for a hypothetical matrix expressing semantic similarity. Then, researchers record participants' neural response to each of the stimuli included with the hypothetical matrices while they are performing a task within the MRI scanner. Next, observed neural dissimilarity matrices are constructed. Observed neural dissimilarity matrices include the same stimuli as the hypothetical matrices, but in these matrices, correlation coefficients reflect dissimilarity between the neural patterns associated with each stimuli comparison. Observed neural dissimilarity can be averaged across voxels within a specified region of interest, or calculated for each voxel using a searchlight approach (Kriegeskorte et al. 2006). Finally, observed neural dissimilarity matrices are correlated with the hypothetical matrices. This enables comparison of a region's BOLD response to hypothesized representational similarity, which allows researchers to characterise the neural representations that are processed within a specified region based on the fit of each hypothetical matrix.

Multivariate approaches show greater sensitivity in discriminating between properties of word stimuli than traditional univariate approaches, as they compare differences in patterns of voxel activity, as opposed to overall levels of neural activation (Oosterhof et al., 2016). Whilst univariate methods can broadly identify regions engaged during cognitive processes, they are less equipped to answer questions around representational content (Kriegeskorte et al., 2006). In comparison, representational similarity analysis extends beyond comparing mean levels of neural activation for different stimuli (Raizada & Kriegeskorte, 2010), as this technique is able to detect differences in neural patterns even when mean activation levels remain constant (Rothlein & Rapp, 2014). By assessing the nature of information encoded within different brain regions during word processing, representational similarity analysis can provide a stronger link between cognitive and neural theories of reading (Fischer-Baum et al., 2017). This approach enables researchers to test competing accounts of how information might be represented in the brain (Evans & Davis, 2015), or to test theories that rely on multiple levels of representation (Fischer-Baum et al., 2017). These insights enable us to contextualise the nature of learned representations and better understand how long-term linguistic knowledge is represented in the brain.

2.2 Statistical approaches

The second half of this chapter outlines some of the statistical considerations applied when conducting the analyses of behavioural work presented in this thesis. Importantly, I discuss differences in approaches across studies. Differences usually arose due to their suitability to answer the research question. In other instances, they may reflect ongoing learning or recent developments in debates surrounding best practice (see Brysbaert & Stevens, 2018, regarding power, or Meteyard & Davies, 2020, regarding reporting of linear mixed-effects models). It may be helpful to state here that the studies in this thesis are not presented in the order in which the work was conducted.[2]

[2] The studies were conducted in the following chronological order: Chapter 5, Chapter 6, Chapter 3, Chapter 4.

2.2.1 Linear mixed-effects models

The majority of behavioural experiments presented in this thesis are analysed using generalised linear mixed-effects models. Linear mixed-effects models are run at observational level, meaning that analyses include every single response as a data point, assuming that outlier removal and other necessary data-cleaning steps have already been completed. Independent variables of interest (e.g. experimental manipulations) are included as fixed effects, whereas variables that are not of interest (such as participant or item variance) are included as random effects (see Meteyard & Davies, 2020, for a more detailed overview). In recent years, linear-mixed effects models have become state of the art when analysing behavioural data, as they offer several advantages over traditional analysis of variance (ANOVA) approaches that have historically been used in language research.[3] There is no loss of data due to aggregation, which results in better statistical power (Brysbaert & Stevens, 2018). Further, linear mixed effects models are better suited for unbalanced designs or coping with missing values, as they are able to weight how much data a particular subject contributes (Baayen, Davidson & Bates, 2008). This is turn provides a better overview of individual differences.

Critically, the random effects structure of linear mixed-effects models permits researchers to measure multiple sources of random variance simultaneously (see Judd et al., 2017). This is in contrast to ANOVA approaches, which can only consider one at a time. ANOVA analyses are performed on aggregated data, which is usually summarised by the average response for each participant in each condition. The error term of the ANOVA then includes variability between participants, both in terms of overall level of performance and the extent to which participants are susceptible to between-condition experimental effects. It is this

[3] Thank you to Dr. Denis Drieghe for a comprehensive introduction to the concepts discussed here, which were outlined in an introductory course on linear mixed-effects models at Southampton University in 2017.

variance that enables researchers to infer whether effects observed within an experimental sample would be observed at population level. However, one limitation of this approach is that it does not account for variability between items. Without considering variability across items, it is difficult to statistically infer whether experimental findings apply beyond the specific linguistic stimuli selected for an experiment to reflect language in general. This is referred to by Clark (1973) as the fixed effects fallacy. In the past, studies have addressed this by including ANOVA statistics conducted separately on both participant and item means (termed F_1 and F_2 analyses respectively). Under this approach, effects are interpreted as meaningful if statistical significance is observed over both F_1 and F_2 analyses. However, this is an imperfect solution. Including an additional test across items introduces further random variance, which increases the chance of a false positive, or Type 1 error. Historically, including F1 and F2 analyses was proposed an intermediate step prior to calculating a quasi-F ratio (F'), that considers both participant and item variability (Clark, 1973). However, this statistic is rarely adopted in practice and has been criticised as being overly conservative (Drieghe, 2017).

Linear mixed-effects models are also more suitable for analysing accuracy data, which is the dependent variable for the majority of experiments presented within this thesis. Accuracy responses are binary categorical variables, as responses can be correct or incorrect. However, this is unsuitable for ANOVA approaches, which are intended for analysis of continuous variables. Generally, researchers address this by calculating mean proportion of accuracy for each participant or item, resulting in a continuous measure of accuracy performance. However, combining two binomially distributed conditions is problematic as the variance within each condition will not be homogenous, which violates an assumption of ANOVA (Jaegar, 2008). Moreover, using converted proportional values may lead to other statistics falling outside of a logically possible range. All proportional data values will fall between the range of 0 and 1, however confidence intervals can extend beyond these values, which could lead to an impossible interpretation (e.g. over 100% accuracy). This is particularly likely for data with very low or very high mean accuracy rates (known as floor or ceiling effects), which we observed in some instances of our data. Linear mixed-effects models are better equipped for accuracy data as they operate at the level of single observations, and can be logistically constructed to handle binomial data.

Linear mixed-effects models provide a powerful and highly versatile method to analyse data, which has led to their rapid adoption within the behavioural sciences. However, a potential downside of this versatility is that it introduces researcher degrees of freedom, and there is ambiguity over what is considered best practice. Meteyard and Davies (2020) demonstrate the extent to which practices diverge in a recent review paper, which reveals "damaging variation" in how models are constructed and reported. The authors highlight that this could create future problems around reproducibility if researchers are unable to synthesize analyses. For example, there is no standardised procedure for fitting linear mixed-effects models to the data. Fitting refers to decisions around which fixed and random effects are included within the model, as well as whether to include interaction terms for fixed effects and whether to include intercepts and slopes for random effects. Some argue that researchers should begin with a maximal structure including all parameters of interest and sources of random variance (Barr et al., 2013), which has the benefit of reducing Type 1 error. However, others assert that maximal models are costly as they can induce a significant loss of power (Matuschek et al., 2017). Including all possible parameters can lead to over-fitting, where the model contains more parameters than can be justified by the data. Including too many unnecessary parameters can also cause convergence issues, where there is not enough data for the model to run and/or form a reliable estimate. Conversely, under-fitting occurs when the model has too few parameters and is too simple to accurately predict effects from the dataset.

In light of these issues, I took several steps in order to be transparent and consistent with our analyses. I defined a maximal structure of our models in advance, with fixed effects based upon our experimental conditions and random effects typically including participant and item variance. I then determined the structure of the optimal model (i.e. the model most appropriate for our data) by systematically adding these random effects, main effects, and interaction terms in turn. At each stage, the model was compared to the model specified in the previous step using likelihood ratio tests, which indicated whether adding each specific element significantly improved the fit of the model. If a specific effect or term did not improve the fit, it was not included within the final optimal model. Within each chapter, I have included the syntax for both the maximal model and (where different) the final optimal model in text, to clearly demonstrate the *a priori* model specification and whether each element specifically contributed to the model fit. I have also made the raw data and scripts available on the Open Science Framework, where the steps taken during model construction can be examined in more detail.

Finally, there is one behavioural study in which linear mixed-effects models were not used to analyse behavioural data, presented in Chapter 5. This is because the study was conducted prior to receiving training on how to implement and analyse data using this statistical method. In this study, behavioural data were analysed using ANOVA instead. One could argue that linear mixed-effects would have provided an advantage for analysing this data, particularly due to the suitability with ANOVA for analysing accuracy data. However, this study does present an interesting case for the importance of modelling both participant and item level variance. The study in question used an artificial language learning paradigm, which enabled precise control over item-level properties within the experiment. Due to this, I believe that the inability of ANOVA to model both participant-level and item-level variance simultaneously is of reduced concern within this study, as the study was investigating reading in an orthography with tightly controlled items. Error variance introduced by items can be governed by counterbalancing item sets, and matching them on variables that also correlate with the dependent variable (Raaijmakers et al., 1999). This enables researchers to rule out the possibility that differences in experimental conditions are due to formerly identified confounding factors. As our design featured novel artificial stimuli, we were able to ensure that stimuli were matched on all factors aside from the critical variable of interest (orthographic density).

2.2.2 Power

Statistical power refers to the probability that a hypothesis test will detect an effect if there is an existing effect to be found. It is dependent upon the effect size, the sample size and the significance level used within a test. Insufficient statistical power increases the risk of failing to detect an existing effect. This is known as a false negative, or Type II error. Therefore, if a study is under-powered, researchers are unable to confidently accept or reject the null hypothesis: there may be no effect, or the design may not have had the power to detect it and make statistical inferences at population level. Power calculations should always be conducted prior to conducting an experiment. Typically, researchers use a hypothetical estimate of the expected effect size to calculate the sample size required to reliably observe such effects if they do appear in the data. Effect size estimates are usually based on those observed in previous literature. The smaller the effect size, the more data required to detect it with adequate power. This is because small effect sizes can otherwise be masked by other random variance within the data. Similarly, larger datasets are required for more complex analyses, such as testing for interactions between variables. Wherever possible, we used a repeated-measures design to reduce participant variance across experimental conditions and thus increase power (see Brysbaert, 2019a).

The studies presented within this thesis take different approaches in terms of power calculations, which is largely due to lessons learned over the time course of the work being conducted. In earlier studies, sample sizes were calculated using the G*Power analysis software for ANOVA (Faul et al., 2007). When conducting these power calculations, I estimated effect sizes by taking those observed from previous literature and then conservatively reducing the estimate (usually by 0.2) in order to account for likely inflation of the true effect size due to publication bias (see Brysbaert, 2019a). I also routinely increased the sample size from the minimum number suggested to allow for exclusion of outliers and full rotations of counter-balanced stimuli. In some cases, sample size was restricted by practical constraints. For example, the sample size for the neuroimaging study presented in Chapter 6 was restricted by research costs due to scanning. Further, there is much less guidance on how to conduct power analyses for neuroimaging research. Instead, I selected the sample size based on previous MRI studies with similar designs, and replaced any excluded participants. I used a similar approach for the artificial language learning study presented in Chapter 5, as data collection for each participant took around ten hours over the course of a week. As a result, data collection was labour intensive and participant compensation was substantial. Sample size was based on samples in previous artificial language learning studies which had a similar timescale and featured tasks in which I expected to observed similar size effects (Taylor et al., 2017; Rastle et al., 2021).

In later studies, I adopted a different approach that was more suitable for calculating power-estimates for linear mixed-effects models. As discussed previously, ANOVA estimates generated by G*Power are less suitable as ANOVA analyses are based on aggregated means rather than observation-level data. Therefore, these power calculations are a very rough fit for analyses conducted by linear mixed-effects models as they do not consider the number of items included within each condition. As Brysbaert (2019) outlines, power can be increased in psycholinguistic research by extending the number of participants in the sample and also the number of items per condition. When analysing at observation-level, a design in which participants are presented with one item per condition is going to be substantially less powered than a design in which participants view 100 items per conditions. I used advice from Brysbaert and colleagues (see Brysbaert & Stevens, 2018; Brysbaert, 2019a and Brysbaert, 2020) as a broad guideline when specifying sample sizes for our experiments analysed using linear mixed-effects models. Brysbaert and Stevens (2018) suggested that 1600 observations for each condition is a good rule of thumb for producing a good level power for an estimated medium effect size ($d = 0.4$).

Later guidance also explains why power calculations should consider how observations are distributed across participants and items (Brysbaert, 2019a). Power is affected by both participant and item level variance; therefore, it is dependent on how reliably the effect is observed across items and participants. Low reliability introduces more variance, which reduces the likelihood of detecting the effect. Brysbaert (2019a) suggests that it is good practice to measure reliability across both parameters, which can be optimised by increasing the number of observations. When designing the studies presented in this thesis, I aimed to ensure that both sample sizes and the numbers of stimuli provided a proportional contribution. For this reason, I avoided using a small sample size with an overly large stimuli set (or vice versa). This had added benefits, as extending the sample size rather than relying on many repetitions of stimuli likely reduced negative influences on task performance, such as fatigue or practice effects.

In my more recent studies, power calculations were conducted via data simulations, using the *simr* package (Green & MacLeod, 2016) in *R* (Core Team 2016). This package has been specifically designed to perform power calculations for linear mixed-effects models and requires the researcher to specify the structure of the model that will be used to analyse the data in advance. As a result, power calculations can be tailored to the exact study design, including incorporation of anticipated variance from random variance. Using this package, I simulated an artificial dataset which included response values for each of our planned experimental conditions. This simulated data set was fitted to the specified linear-mixed effects model. I then ran a series of Monte Carlo power simulations across a range of effect sizes and sample sizes. For each simulation, a statistical test indicated the fit of the model to the data and the observed power estimate. I used two different approaches to conduct these power simulations. Firstly, I ran simulations where our effect sizes were fixed but sample size was modified, in order to determine the required sample size to observe an effect of this size with sufficient power. Secondly, I used the reverse approach to estimate the effect sizes that I would have adequate power to reliably detect with a specific sample size.

When conducting power analyses, I regularly found it difficult to find a reliable estimated effect size, either due to lack of reporting in previous literature, or because there was no clear blueprint to base my study upon. For example, in Chapter 5 I conducted an artificial language learning study on the transposed-letter effect. Previously reported transposed-letter effects have usually been for masked-priming studies within a reader's native language; therefore, I did not think the effect sizes would be translatable to an unprimed lexical decision task in a newly acquired orthography. Going forward, in situations where there is not a clear estimate effect size, I would opt to also use Brysbaert and Steven's (2018) criteria of at least 1600 observations per condition as a secondary rule of thumb.

Simulations were the most effective method for sample estimates, particularly for studies using linear mixed-effects models. They enabled specificity based on the exact model structure, rather than broad estimates based on number of conditions. This was particularly beneficial when conducting power calculations for more complex analyses, such as those including interactions. Despite the benefits of power simulations, it was not appropriate to go back and perform uniform power simulations across the studies in the thesis post-hoc, as conducting power analyses on observed data violates two main assumptions (Dziak et al., 2018). Firstly, statistical power reflects the probability of rejecting a null hypothesis, based on estimates of parameters (e.g. effect sizes and variance) at population level (Cohen, 1992). However, power analyses do not predict the probability of a future outcome if they are performed on a test that has already been conducted on existing data. Secondly, power estimates are calculated using sampling distribution, which forecasts probability over a range of possible samples. Post-hoc power analyses are based on a single specific sample rather than a sampling distribution. Consequently, post-hoc power estimates can be misleading, and provide redundant information at best. Dziak et al. (2018) convey this with a quote by Goldstein (1964, p.62): "If the axe chopped down the tree, it was sharp enough".

2.3 Open science

Each of the studies presented in this thesis has an accompanying open-access project page on the Open Science Framework, which is linked within each chapter. For ease of reference, they are also listed below:

- Chapter 3: https://osf.io/z8qhv/?view_only=b19d759683e44d5faff524e3da5c5cd4
- Chapter 4: https://osf.io/p4q9u/?view_only=8485d54437b8473d92d1d50c37512fa0
- Chapter 5: https://osf.io/g74vp/ (public)
- Chapter 6: https://osf.io/yczpu/?view_only=59e65836bb6e49c5871a885d4d855efa

For each study, I have included a full list of the stimuli and in the majority of cases I have included the scripts or files required to run experimental tasks. I have also included all observation-level data for behavioural tasks. This is prior to removing outliers or any transformations, although in some instances the raw data output has been combined for easier usability. For example, the experimental program DMDX (Forster & Forster, 2003) produces an individual .azk file for each participant, in which each trial has a numerical code relating to the item number, condition and the correct response. These files have been concatenated into a single .csv file, and numerical codes have been converted into meaningful descriptive columns. These processing procedures were scripted in R, which allowed the procedure to be automated and traceable. I aimed to make our data as open as possible, with the exception of raw MRI data in order to preserve participant anonymity.

Within this thesis, all analyses were scripted where possible. This was prioritised in order to promote replicability and transparency as much as possible. Analyses were primarily conducted within R, and as with the data, accompanying scripts were published on the Open Science Framework. All scripts are fully annotated, and the level of detail has increased as my expertise in R has developed. For example, the scripts published with Chapter 5 are standard R scripts which contain the lines of code required to reproduce the statistics in the chapter. In later studies, I have used R Markdown to provide a more sophisticated commentary of analysis decisions made, which also produce a report of the results as an output (see the corresponding

OSF page for Chapter 6 as an example). fMRI analyses were conducted in MATLAB, as a requirement for fMRI analysis toolboxes in SPM (Friston et al., 1994) and CoSMo MVPA (Oosterhof et al., 2016). These analyses are also scripted, and the analysis pipeline is again published on the Open Science Framework.

2.3.1 Pre-registration

The work presented in Chapters 3 and 4 was also pre-registered on the Open Science Framework prior to data collection. Pre-registration is based on the premise that researchers publish detailed specifications on their hypotheses, the accompanying experimental design and planned analyses prior to viewing the data. Pre-registration is growing in popularity as an open science practice as it increases transparency by preventing researchers from under-reporting flexibility in data analyses (Nosek et al., 2018). Further, recording hypotheses in advance encourages researchers to make sure that hypotheses are specific, and that the experimental design is suitable. As a result, pre-registration can reduce instances of researchers *HARKing*, or hypothesizing after the results are known (Kerr, 1998). This can occur intentionally or unintentionally for a variety of reasons (see Bishop, 2020). The original hypotheses may not have been specific enough, which could lead to ambiguities in interpretation. Alternatively, the data may not support the hypothesis but may align with an alternative post-hoc interpretation. Importantly, pre-registration does not prohibit researchers from conducting post-hoc analyses or forming alternative interpretations of the results. The difference is that deviations from the original plans are openly reported, allowing for a clearer distinction between confirmatory and exploratory analyses. In previous research, this distinction has often been blurred, which has led to issues in reproducibility and replicability (Bishop, 2020).

Pre-registration increased accountability and required thorough consideration of how each stage of the research pipeline would be conducted. Prior to data collection, I simulated data and plotted multiple potential outcomes based on my parameters of interest. This exercise was instrumental in scrutinising my hypotheses. As well as ensuring that hypotheses were precise and testable, I was able to conceptualise various alternative outcomes and the theoretical reasons as to why they may occur. I also used data simulation to script the entire analysis pipeline before the data was collected. This allowed exact specification on how the data would be cleaned, how statistical models would be constructed and the exact syntax for how the data would be analysed. To a certain extent, simulated data enabled me to check for any bugs in the scripts and ensure that analyses and visualisations produced the information required to optimally test the hypothesis. This reduced the need for modifications to analyses after viewing the data. Front-loading this work increased overall efficiency. The time required to construct the analysis pipeline provided extra time to reflect on the conceptual validity of hypotheses and the experimental design, which enabled improvements which could only have been made ahead of data collection. Conversely, the time required for analyses after data collection was drastically reduced as the pipeline was already in place.

Importantly, pre-registration does enable researchers to deviate from original research plans if required. For example, in the pre-registration for one of the experiments presented in Chapter 3, I stated that I would exclude participants with an overall d' prime accuracy score that was lower than zero. This was equivalent to 50% accuracy, or chance performance, as the task had a two-alternative forced choice paradigm. When considering multiple outcomes, I had predicted that participants would have lower accuracy in one condition compared to others. However, we had not anticipated the observed result: an inhibition effect so large that almost all participants were significantly below chance in a particular condition. In fact, the mean accuracy rate for this condition was so low (28%) that it dragged down mean participant performance to be at or below chance level for most participants. Clearly in this case, our exclusion criteria were unsuitable as overall participant performance was the result of a large and highly consistent experimental effect. Therefore, I opted to report the results without excluding participants on this basis.

In some ways, this deviation further highlighted the importance of being transparent about the thought process when the study is conceptualised. Once I had observed this very large inhibition effect (which then consistently occurred in follow-up studies), it was much harder to maintain the mindset of our original predictions. However, our pre-registration served as a time-stamped reminder that we had not expected this effect. This was extremely helpful when writing up the study, as we ensured that our rationale and hypotheses reflected our thinking prior to data collection. Of course, an important part of writing up scientific research is providing the reader with a narrative and the appropriate context for the findings later reported. However, this runs the risk of setting up the reader for the observed result, rather than outlining the original motivation. I believe that pre-registration was especially valuable for reducing this bias when reporting our findings.

CHAPTER THREE: LETTER IDENTIFICATION IN SENTENCE CONTEXT

How does sentence context influence the precision of letter identification?

Lally, C. & Rastle, K. (in revision). How does sentence context influence the precision of letter identification?

3.1 Abstract

Readers understand sentences by recognizing individual words, and they recognize words by analysing constituent letters. Readers rarely encounter words presented in isolation, yet there is remarkably poor understanding of how we recognize letters beyond single word contexts. Previous research has demonstrated that readers are more accurate at identifying letters when they appear in a real word (e.g. *plane*) compared to a pseudoword (e.g. *plave*), a phenomenon known as the word superiority effect. The present study investigated how the word superiority effect manifests within various sentence contexts. Our findings across six experiments revealed substantial fluctuations in the size of the word superiority effect across sentence contexts. Most importantly, the word superiority effect was abolished when the target did not align with readers' expectations. These findings suggest that the precision of orthographic processing depends on the perceived accuracy with which words can be anticipated from sentence context. The current work highlights the need for an integrated model that considers basic orthographic processes within meaningful sentence contexts.

All experiment materials, data, and analyses are available on the Open Science Framework: https://osf.io/z8qhv/?view_only=b19d759683e44d5faff524e3da5c5cd4/.

3.2 Introduction

Readers are more accurate at identifying letters when they appear in the context of a real word (e.g. *plane*) compared to a pseudoword (e.g. *plave*) (Reicher, 1969; Wheeler, 1970; Grainger & Jacobs, 1994; Coch & Mitra, 2010; Kezilas et al., 2016). This *word superiority effect* is demonstrated using a Reicher-Wheeler task (Reicher, 1967; Wheeler, 1970), in which participants briefly view a word or pseudoword before deciding which of two letters appeared in the string. The task is structured to minimise post-hoc guessing by using foil letters that always result in a string with the same lexical status as the target (e.g. letters *n* or *d* for target word *CROWN*). The word superiority effect is typically interpreted as evidence that word representations enhance letter identification processes.

The word superiority effect is a cornerstone of theories proposing to explain how we recognize single words, including the Interactive Activation Model (McClelland & Rumelhart, 1981) and the Multiple Read-Out Model (Grainger & Jacobs, 1996). However, we rarely encounter words presented in isolation; and there is remarkably poor understanding of how we recognize letters beyond single word contexts. In the current work, we sought to bridge the gap between single word and sentence level reading by investigating how the word superiority effect is influenced by word predictability within a sentence (e.g. *the rocket returned from outer space/spade*). We aimed to establish whether expectations from sentence context influence letter-identification processes.

Our findings across six experiments indicate that the word superiority effect is modulated by properties of sentence context. Specifically, in sentence contexts in which readers can reliably anticipate the upcoming word, the word superiority effect is abolished if the target string does not match the reader's expectation. In contrast, the word superiority effect is obtained when target strings are presented in isolation and in neutral sentence contexts that do not strongly constrain readers' predictions. Overall, these findings suggest that predictability from sentence context influences the precision of orthographic processing within individual words. The current work highlights the need for an integrated model that considers basic orthographic processes within meaningful sentence contexts.

3.2.1 The word superiority effect in models of visual word recognition

Two of the most influential computational models of visual word recognition are the Interactive Activation Model (McClelland & Rumelhart, 1981) and the Multiple Read-Out Model (Grainger & Jacobs, 1996). Both of these models propose mechanisms to account for the word superiority effect.

The Interactive Activation Model (McClelland & Rumelhart, 1981) consists of three interactive processing levels: feature detectors, letter detectors and word detectors. Letter detectors are activated through bottom-up input from the feature detectors, and the perceptibility of individual letters increases through feedback from top-down word representations. Word nodes send excitatory feedback to letter nodes that correspond with letters that are present in the word, and inhibitory feedback to letter nodes that are not present in the word. Pseudowords, which do not have pre-existing word representations, do not provide this top-down activation benefit. This enhanced activation increases the perceptual salience of letters occurring within words, and thereby facilitates their selection in the Reicher-Wheeler task. In contrast, the Multiple Read-Out Model (Grainger & Jacobs, 1996) proposes that letter identification occurs when the activation for an appropriate letter *or* whole-word representation reaches a critical level. According to the Multiple Read-Out Model, the word superiority effect arises because shorter durations are required to activate whole word representations compared to individual letter representations. Readers are less accurate at identifying letters in pseudowords compared to words, as there is no corresponding word representation; therefore, readers can only identify letters once the individual letter representations have been activated.

Whilst the Interactive Activation Model and the Multiple Read-Out Model explain the word superiority effect in different ways, both propose that letter identification will always be superior in words compared to pseudowords because of the activation of word-level representations. However, these models refer to words presented in isolation; they have nothing to say about how we recognize letters in sentence contexts. This is a major deficiency since there is strong evidence that word activation is constrained by sentence-level factors. In the next section, we review the literature before considering how sentence context might influence the word superiority effect.

3.2.2 Word recognition in sentence contexts

There is extensive evidence that readers use sentence level information during word recognition. Readers are better at recalling grammatical sentences compared to scrambled lists of the same words (Baddeley et al., 2009, Toyota, 2001), and are more accurate at recognising words in grammatical sentences compared to ungrammatical sentences (Snell & Grainger, 2017). Further, readers are less likely to notice transposed word effects if the words can be re-arranged to form a grammatical sentence (*the white was cat big*) than if they cannot (*the white was cat slowly*; Mirault et al., 2018).

Semantic predictability also facilitates word recognition. Asano and Yokosawa (2011) reported increased word recognition accuracy when a word appeared in a semantically plausible context (*I write a column to be published in a newspaper*) compared to an implausible context (*I write a column to be published in a vegetable*). Predictability is typically defined by a word's *cloze probability*: a metric that describes the likelihood of a word occurring in a specific context. This metric may be calculated from sentence corpus data (e.g. Potsdam Sentence Corpus; Boston et al., 2008) or from cloze tasks, where participants are given an incomplete sentence or phrase, and asked to predict the final word (Taylor, 1953). For example, if the sentence frame was "The bartender poured a pint of ____", and 87 out of 100 people responded with "beer", the cloze probability of "beer" would be 0.87 in this context.

Word predictability has a reliable influence on eye-movements during reading (see Staub, 2015 for a review). Previous eye-tracking studies have found that the eyes are more likely to skip over predictable words than unpredictable words (Ehrlich & Rayner, 1981; Altarriba et al., 1996; Rayner & Well, 1996; Rayner et al., 2011; Frisson, Rayner & Pickering, 2005). Predictable words also tend to elicit shorter fixation times than unpredictable words (Zola, 1984; Balota et al., 1985; Rayner & Well, 1996; McDonald & Shillcock, 2003; Frisson et al., 2005; Rayner et al., 2011). These findings show that readers spend less time looking at predictable words, which suggests that they are less effortful to process than unpredictable words.

Predictability also facilitates online word processing in electrophysiological data. ERP recordings typically show a negative peak during semantic processing, around 400 ms after the onset of a word is presented within a sentence, known as the N400 (see Van Petten & Luka, 2012; DeLong et al., 2014 for a review). Kutas and colleagues have consistently shown that the amplitude of the N400 response is increased (Kutas & Hillyard, 1983; Kutas & Hillyard, 1984; Federmeier & Kutas, 1999; Federmeier et al., 2007; Kutas & Hillyard, 1984) or delayed (Kutas & Hillyard, 1980) in the event of a low cloze probability, or unexpected, word. The influence of word predictability on the N400 adds another dimension of evidence. ERP recordings not only support a predictability advantage, but also reveal an unpredictability cost.

Other ERP studies have demonstrated that it is not just predictable words that benefit from ease of processing, but also words that are related to them. For example, Federmeier and Kutas (1999) found that N400s were reduced for unpredictable words that were semantically related to the predicted target (*The captain kicked the baseball*), but not for unpredictable words that were unrelated to the predicted target (*The captain kicked the orange*). Similarly, Lazslo and Federmeier (2009) found higher N400 amplitudes for neighbours of the predicted word (*before lunch he has to deposit his pay check at the bank/bark/pank/bxnk*) compared to strings with no letter overlap (*the genie was ready to grant his third and final wish/clam/horm/rqck*). Remarkably, these effects persisted across pseudowords and illegal consonant strings, which indicated that the neighbourhood advantage occurred regardless of lexical status.

Multiple paradigms provide converging evidence that predictability from sentence context facilitates word recognition. Critically, online measures demonstrate that predictability influences the earliest stages of word recognition, as shown by eye-movements, such as skipping, and ERP data. Staub (2015) proposed that "pre-activation of a potential upcoming word may facilitate the extraction of the visual features and letters in that word, and identification of a word's orthographic form" (p. 323). In other words, predictability is likely to be a strong contributor in determining the word candidates that inform letter identification.

3.2.3 Predictability and letter identification

These findings concerning predictability reveal why it is important to think about letter identification processes in the context of sentences as opposed to single words. In single word context, the reader does not have a prior expectation as to what the word will be. Therefore, the word representations that boost letter identification will be based on the closest match to the visual input. In contrast, sentence context offers potential for readers to form predictions and narrow the pool of word candidates prior to recognising a particular word. This impact on activation of word candidates is likely to have implications on letter recognition. However, letter recognition processes are rarely considered within models of sentence reading, because these models tend to see words as the smallest units of representation (Snell et al., 2018).

One possibility is that predictability *boosts activation* for expected upcoming word representations. This would result in increased feedback from word nodes (and inhibition from competitors) to letter nodes in the Interactive Activation Model, and reduced time to activate word representations in the Multiple Read-Out Model. Both explanations would predict increased letter identification accuracy in predictable words compared to unpredictable words. However, both models still predict letter identification to be more accurate in all words compared to pseudowords, as even unpredictable words have a pre-existing lexical representation that can be activated to support letter identification. In summary, an activation account would forecast that predictability may increase the size of the word superiority effect in some word candidates over others (i.e. those that are highly predictable from sentence context), but we would expect to observe a word superiority effect for all words within a sentence context.

However, the impact of pre-activation on letter identification could be more complex. When a predictable word is pre-activated, it is highly likely that competition effects will inhibit similar words, such as orthographic neighbours. For example, the Interactive Activation Model posits that activated word nodes compete with all other word nodes through excitation and inhibition (Rumelhart & McClelland, 1982). An activated word node sends feedback excitation to letters that are consistent with it and inhibition to letters that are not. Similarly, the Multiple Read-Out Model proposes that multiple orthographic representations compete in the identification of a letter string. Grainger and Jacobs (1993) described this as the lexical inhibition hypothesis, as inhibitory connections are used to determine the best match. Pre-activation has the potential to skew competition effects, providing our first indication that the weight assigned to various letter identification cues may shift based on whether a word appears in isolation or in sentence context. Pre-activated representations may introduce not only a letter identification advantage in predictable words (*the calm pilot landed the faulty plane*), but also a distinct disadvantage for letter identification in unpredictable words (*the calm pilot landed the faulty plate*). Consequently, the word superiority effect may be reduced, or even eliminated, when a word is not expected from sentence context.

Sentence reading models, including the E-Z Reader (Reichle et al., 2003), the SWIFT model (Engbert et al. 2002; Engbert et al. 2005), and the OB1 model (Snell et al., 2018) give further reason to predict this outcome. These models suggest that predictability not only increases the activation of upcoming word representations, but also reduces the threshold of evidence required for word recognition. Whilst activation refers to how well an orthographic representation aligns with the input, the threshold refers to how accurate the alignment must be in order for the representation to be accepted. This is an important criterion in order to ensure efficiency in sentence reading. If the threshold is too high, reading is time-consuming and effortful. If the threshold is too low, readers are prone to making mistakes.

The models propose that the threshold required for successful word recognition is based upon the cloze probability of potential upcoming words. The E-Z Reader and SWIFT models include a stage in which preliminary information on an upcoming target informs the selection of potential word representations, which are then used to set the threshold for word recognition. The degree of certainty with which the upcoming word can be predicted modulates the processing time dedicated to word recognition. Both models assert that more extensive processing may even be skipped if predictability cues provide a strong enough prior. In the E-

Z Reader model, Reichle, Rayner and Pollatsek (2003, p. 452) state that "words that can be predicted with complete certainty within a given sentence context will require no time in this second stage [….] such cases reflect the situation when top-down information has already fully activated the semantic and phonological codes given reasonable corroborating input from orthography". In the SWIFT model, Engbert et al. (2005, p.12) assert that "processing rate is decreased during preprocessing […] this assumption is motivated by the fact that for a high-predictable word there is a high probability that the word can be guessed without (or with minimal) visual input". The OB1 reader does not explicitly include a pre-processing stage, although predictability is proposed to influence potential target selection prior to fixation. Snell, van Leipsig, Grainger and Meeter (2018, p. 974) state that "recognized words generate expectations about upcoming words, through feedback activation of word nodes based on cloze-probability" and word recognition occurs when there is a "successful match" under a variable recognition threshold based on word frequency and cloze probability. Under these assumptions, letter-level processing may be less precise if the reader is able to reliably anticipate the upcoming word.

Each of these models propose that word recognition thresholds are determined by the likelihood of predicting a word from other words within the sentence. The likelihood of a specific word occurring is described by its cloze probability; however, it is impossible for the reader to use this information to set the threshold prior to word recognition, as knowing the cloze probability of the actual upcoming word cannot be known ahead of the word being recognised. Instead, thresholds can be determined by the cloze probability of the most likely word candidate, or *contextual constraint*, which refers to how many potential words are predicted from a sentence frame (Staub, 2015; Staub et al., 2015). High constraint contexts tend to predict a single word with high cloze probability ('*the rocket soared into outer <u>space</u>*'), whereas low constraint contexts have many plausible low cloze probability forms of continuation (*the children were learning about* space). High constraint contexts predict a single or smaller number of potential word candidates; therefore, there is a reduced risk of error from a lower evidence threshold. In contrast, low constraint sentences have many possible word candidates, therefore readers are expected to use a more stringent threshold in order to distinguish between them. As a result, high constraint contexts are likely to evoke a lower threshold than low constraint contexts.

Based on these assumptions, we would expect thresholding to have critical implications for letter identification and the word superiority effect. We propose that contextual constraint determines how stringent the threshold is, and cloze probability predicts whether letter identification under the threshold will be successful. The word superiority effect is consistently observed in single word context, as contextual constraint and cloze probability cues are unavailable. Therefore, the threshold for word recognition remains at its highest and is based upon the closest match to any known word representation. Further, the word superiority effect will be consistently observed in low constraint sentences, regardless of cloze probability. Because low constraint sentences do not narrow the pool of possible pre-activated targets, the threshold must remain high and any known word representation can be used to support letter identification, in a similar manner to single word recognition. In contrast, the word superiority effect may only be observed in high constraint sentences if the target has high cloze probability. This is because high constraint contexts lower the threshold for word recognition to a good enough match as the reader has a strong prior for the upcoming word. We would expect to observe the word superiority effect in high cloze probability (or predictable) words, as letter identification would benefit from the predicted word representation prioritised for the good enough match. However, lowering the threshold would have detrimental consequences for letter identification in words with low cloze probability. In the event of this, low cloze probability (or unpredictable) words would incur a triple recognition cost. Firstly, word representations cannot support letter identification if the target does not correspond with the predicted good-enough match. Secondly, the word representation that corresponds with the actual target is likely to have received competitive inhibition due to the pre-activation of a more predictable representation. Finally, the lower threshold means that readers are more likely to miss the fine-grained letter information required for distinguishing between word neighbours. Therefore, when there is a clear predictable candidate, the word superiority effect will only be observed if the word is predictable from the sentence context.

3.2.4 Research aims

The current work explores the word superiority effect beyond single word context, in order to investigate how sentence level expectations influence letter recognition. We conducted a series of experiments measuring letter identification accuracy in word and pseudoword neighbours (e.g. *plane-plate-plave*). Across each experiment, these neighbours appeared in different sentence contexts in order to systematically modify and distinguish between effects of cloze probability and contextual constraint. In Experiment 1, we replicated the word superiority effect when targets were presented in isolation. In Experiment 2 and 3, we examined whether the word superiority effect was dependent on cloze probability, by presenting neighbours with high and low cloze probability within the same high constraint sentence context (e.g. *the calm pilot landed the faulty plane/plate/plave*). In Experiment 4, we investigated whether predictability effects were diminished when cloze probability and contextual constraint were reduced through word order disruption (e.g. *landed the pilot the faulty calm plane/plate/plave*). In Experiments 5 and 6, we presented the target neighbours in sentence contexts where word targets were matched for cloze probability, and instead varied contextual constraint. This enabled us to investigate whether the word superiority effect was observed in low cloze targets across high and low constraint contexts (e.g. *the boy admired the smooth white* <u>*plane/plate/plave*</u> *vs. the dog ran from the venomous* <u>*plane/plate/plave*</u>).

We hypothesized that predictability *increases activation* and *reduces the threshold* of evidence required when an upcoming word is expected from sentence context. As a result, the word superiority effect should be observed only if the word has high cloze probability, or appears in a low constraint context. In contrast, letter identification accuracy will be reduced in low cloze probability words in high constraint contexts, as a less precise threshold would increase the likelihood of errors in words that are unexpected from sentence context. Pre-registration, stimuli, experiment scripts, observation-level data and analysis scripts for all experiments are available on the Open Science Framework.

3.3 Experiment 1

The initial experiment aimed to replicate the word superiority effect in the absence of a sentence context. We predicted that readers would be more accurate at identifying letters in words compared to pseudowords (Kezilas et al., 2016; Coch & Mitra, 2010; Grainger & Jacobs, 1994).

3.3.1 Method

3.3.1.1 Participants

Twenty-four monolingual English speakers (17 female, 7 male) completed the experiment at Royal Holloway University of London, in exchange for £5. Participants were aged 18-35, with normal or corrected-to-normal vision, and no previous history of reading difficulty. The sample size was computed using an a priori G*Power analysis (Faul et al., 2007). Previous literature regarding the word superiority effect suggested an effect size of 0.6 (Grainger et al., 2003); we reduced this to 0.4 in order to account for possible publication bias (Brysbaert & Stevens, 2018). The parameters of alpha were set to 0.05 and power was set to 0.95.

3.3.1.2 Stimuli

Stimuli for the main experimental task consisted of 90 words and 90 pseudoword neighbours (e.g. *plate – plave*). The words were all nouns between four and six letters long, with a frequency between 0 and 170 words per million (CELEX Lexical Database; Baayen et al., 1995), and with between 2 and 21 neighbours (Coltheart's N; Coltheart et al., 1977). Target pseudowords were pairwise-matched to their word neighbours for word length (4-6 letters) and neighbourhood density (2-21). Stimuli for a preliminary staircase-thresholding task consisted of an additional 20 words and 20 pseudowords, with the same properties as those used for the main task. None of the stimuli presented in the thresholding task were present in the main task.

3.3.1.3 Procedure and apparatus

Participants provided informed consent prior to completing a Reicher-Wheeler task (Reicher, 1969; Wheeler, 1970) consisting of 90 trials, administered using DMDX (Forster & Forster, 2003). Participants received a self-paced break halfway through the experiment. Participants were tested individually in a quiet room, seated approximately 40cm from an 18-inch CRT monitor. The screen had a refresh rate of 60 Hz (16.67 ms), and the exposure duration for each stimulus was a multiple of the refresh rate. All stimuli were displayed in white on a black background in size 14 Courier New font.

Within each trial, participants viewed a 500 ms fixation cross, followed by a forward mask for 33 ms. A word or pseudoword then appeared for a predetermined duration (see below), before a hash symbol (#) backward-masked each letter of the target. For the first 100 ms duration of the backwards mask, a probe bar (|) appeared above and below one of the symbols, which indicated that the participant should identify the letter in the specified position. A target letter and a foil letter then replaced the probe bars in the same position above and below the backwards mask. The target letter corresponded to the letter that appeared in that position within the target stimulus, whereas the foil letter did not appear within the target stimulus at all. The participant had 5000 ms to make a button-press response indicating which of the two letters they believed was present within the target. Participants completed five practice trials prior to completing the main task. Targets were counterbalanced to ensure that participants received an equal number of word and pseudoword targets, and that participants saw only one of each target pair across word and pseudoword conditions. Foil letters presented for word targets always yielded another word, while foil letters presented for pseudoword targets always yielded another pseudoword.

Target exposure duration was determined for each participant based on performance in an initial staircase-thresholding task (adapted from Davis, 2001), which used the same trial procedure and mask durations as the main task. In the thresholding task, exposure duration began at 33 ms, and was adjusted after each response. If the participant correctly identified the target letter, exposure duration was reduced by 17 ms (one tick). If the participant incorrectly identified the foil letter, exposure duration was increased by 17 ms. Exposure duration was held constant after twelve changes in direction, and this value set the target exposure duration for each participant in the main experimental task. Based on performance in the preliminary thresholding task, exposure during the main experiment was 33 ms (two ticks) for 11 participants, 50 ms (three ticks) for 11 participants and 83 ms (five ticks) for two participants. These exposure durations were similar to previous Reicher-Wheeler studies with skilled adult readers (e.g. Chase & Tallal, 1990; Grainger et al., 2003; Lété & Ducrot, 2008; Coch & Mitra, 2010; Kezilas et al., 2016).

3.3.2 Results

Accuracy data were modelled using the lme4 package (Version 1.1-12, Bates et al., 2015) in R (Version 3.3.1; R Core Team 2016). We used a logistic general linear mixed-effects model (GLMM) with the following structure: glmer(Accuracy ~ Word Status + (1|Participant) + (1|Item) + (1|Exposure), family = binomial). Beta (β) and odds ratios (*OR*) are used to report effect sizes. β is the logit transformed fixed effect coefficient, which refers to the estimated difference between conditions having controlled for random effects. *OR* (derived from β) measures the difference in odds of being correct (versus incorrect) in one level of a fixed effect compared to another.

The data are visualised in Figure 1. Accuracy rates were significantly higher for word targets relative to pseudoword targets ($\beta = 0.65$, $OR = 1.91$, $SE = 0.11$, $Z = 5.79$, $p < .001$).

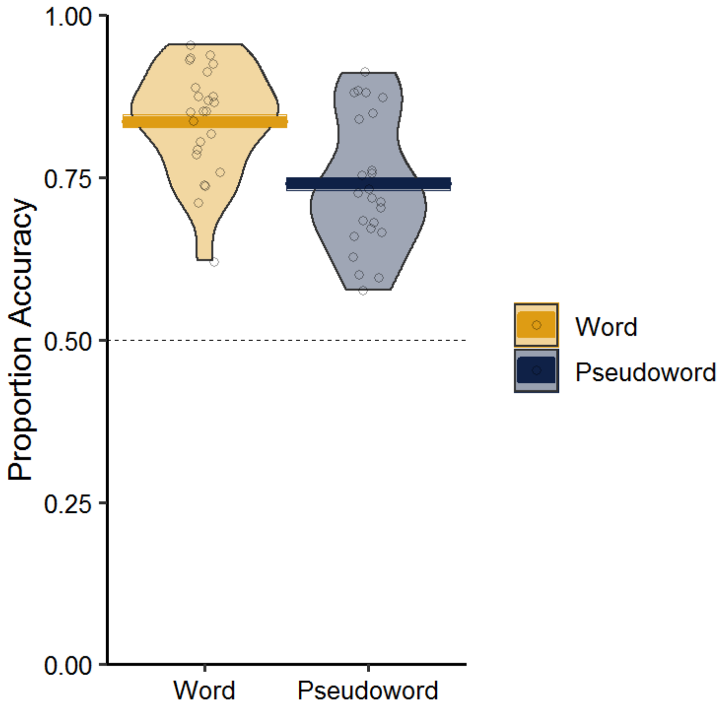

Figure 1. Mean accuracy rates for Experiment 1. Crossbars display mean accuracy rates across participants and the surrounding tiles display one standard error from the mean, calculated for within-subject designs (Loftus & Masson, 1994). Data points display accuracy rates for individual participants and violins demonstrate the distribution of the data. The dotted horizontal line indicates chance performance.

3.3.3 Discussion

Experiment 1 replicated the word superiority effect, as participants were more accurate at identifying letters in real words compared to pseudowords. The odds ratio demonstrates that the odds of selecting the correct letter were 1.91 times more likely in words compared to pseudowords. The results support both the Interactive Activation Model and Multiple Read-

Out Model predictions that in single word contexts, activation for pre-existing word representations enables increased letter identification accuracy within a limited timeframe.

3.4 Experiment 2

In Experiment 2, we investigated the influence of cloze probability on the word superiority effect in a sentence context. Orthographic neighbours were presented at the end of high constraint sentences, in which one of the neighbours had high cloze probability. We expected letter identification accuracy to be higher in predictable words compared to unpredictable words, due to increased pre-activation from sentence context. The preceding sentence frames predicted a high cloze probability target; therefore, we anticipated that readers would use a lower threshold, and accept a good-enough match to the expected word, rather than the closest match to any known word. Therefore, we predicted that unpredictable words would not show a word superiority effect in highly constrained contexts.

3.4.1 Method

3.4.1.1 Participants

This experiment included 24 participants (19 female, 5 male) from the same population as tested in Experiment 1. None of the participants were included in previous or subsequent experiments in this series.

3.4.1.2 Stimuli

Stimuli for the main experimental task consisted of the same 90 pairs of words and pseudoword neighbours as were used in Experiment 1 (e.g. *plate – plave*). Each pair was extended to include an additional one-letter different word neighbour (e.g. *plane – plate – plave*). These triplets were assigned to a sentence frame, so that the final word of the sentence frame was either highly predictable (*the calm pilot landed the faulty plane*), unpredictable (*the calm pilot landed the faulty plate*) or a pseudoword (*the calm pilot landed the faulty plave*). The target stimuli assigned to the unpredictable and pseudoword conditions of Experiment 2 were the same target stimuli assigned to the word and pseudoword conditions in Experiment 1.

Sentence frames consisted of seven words and 35-40 characters. Targets were group-wise matched for CELEX frequency (Baayen et al., 1995), neighbourhood density and word length (Table 1). Predictable and unpredictable target pairs were checked for semantic relatedness using latent semantic analysis (LSA; Landauer & Dumais, 1997), to ensure that they did not share a similar meaning (*M*: 0.08, *SE*: 0.01).

Table 1.
Stimulus properties for words and pseudowords.

Property	**Predictable**	**Unpredictable**	**Pseudoword**
Word length	5.3 *(0.05)*	5.3 *(0.05)*	5.3 *(0.05)*
CELEX frequency	34.72 *(3.43)*	35.38 *(4.37)*	--
Neighbourhood size	8.58 *(0.43)*	8.79 *(0.49)*	7.66 *(0.42)*

We obtained metrics of predictability by running a sentence cloze task. The task was administered online using Qualtrics (2019), with an independent sample of 42 participants sharing the same characteristics as the main experimental sample. Participants read sentence frames one at a time, and predicted the final word of the sentence by typing into a blank text box. We measured contextual constraint of the sentence frame by the proportional frequency of the most common response. Across each sentence frame, the most common response had a mean cloze probability of 0.76 (*SE*: 0.02). This indicated that the sentence frames had high contextual constraint. We measured cloze probability of the targets by the proportional frequency of responses that aligned with either word target. Predictable targets had a mean cloze probability of 0.76 (*SE*: 0.01), whereas unpredictable targets had a mean cloze probability of 0.00 (*SE*: 0.00). Participants provided the same word as the predictable target the majority of the time and never provided the same word as the unpredictable target.

3.4.1.3 Procedure and apparatus

Experimental apparatus was identical to that used in Experiment 1. Participants completed a rapid serial visual presentation (RSVP) Reicher-Wheeler task consisting of 90 trials preceded by five practice trials. Each trial began with a 500 ms fixation cross, followed by a sentence frame presented one word at a time, with each word presented for 150 ms. Participants then viewed a 33 ms forward-mask before the target stimulus appeared. The target stimulus was displayed for a variable duration based upon the preliminary thresholding procedure. After the duration had elapsed, the target was backward masked by hash symbols. A probe bar appeared above and below one of the hash symbols for the first 100 ms, and was subsequently replaced by a target letter and a foil letter. The participant then had 5000 ms to make a button-press response indicating which of the two letters they believed was present in the target.

Counterbalanced lists ensured that participants saw an equal number of predictable, unpredictable and pseudoword targets, and that each sentence frame was presented only once. Foil letters for word targets always corresponded to the non-target word within a triplet. This meant that unpredictable targets had foil letters that would result in a predictable construction, while predictable targets had foil letters that would result in an unpredictable construction. Foil letters for pseudoword targets resulted in another pseudoword.

Exposure duration for target stimuli was determined for each participant using the same initial staircase-thresholding task described in Experiment 1. Exposure duration for participants in Experiment 2 was 33 ms (two ticks) for 14 participants, 50 ms (three ticks) for seven participants, 67 ms (four ticks) for two participants, and 83 ms (five ticks) for one participant.

3.4.2 Results

Accuracy data were modelled using a GLMM with the following structure: glmer(Accuracy ~ Predictability + (1|Participant) + (1|Item) + (1|Exposure), family = binomial). Data are visualised in Figure 2.

Accuracy was significantly higher for predictable targets compared to unpredictable targets, $\beta = 2.80$, $OR = 16.49$, $SE = 0.14$, $Z = 19.93$, $p < .001$, and pseudoword targets, $\beta = 1.65$, $OR = 5.21$, $SE = 0.13$, $Z = 12.40$, $p < .001$. Accuracy was significantly lower for unpredictable targets compared to pseudoword targets, $\beta = -1.15$, $OR = 0.32$, $SE = 0.12$, $Z = -10.01$, $p < .001$.

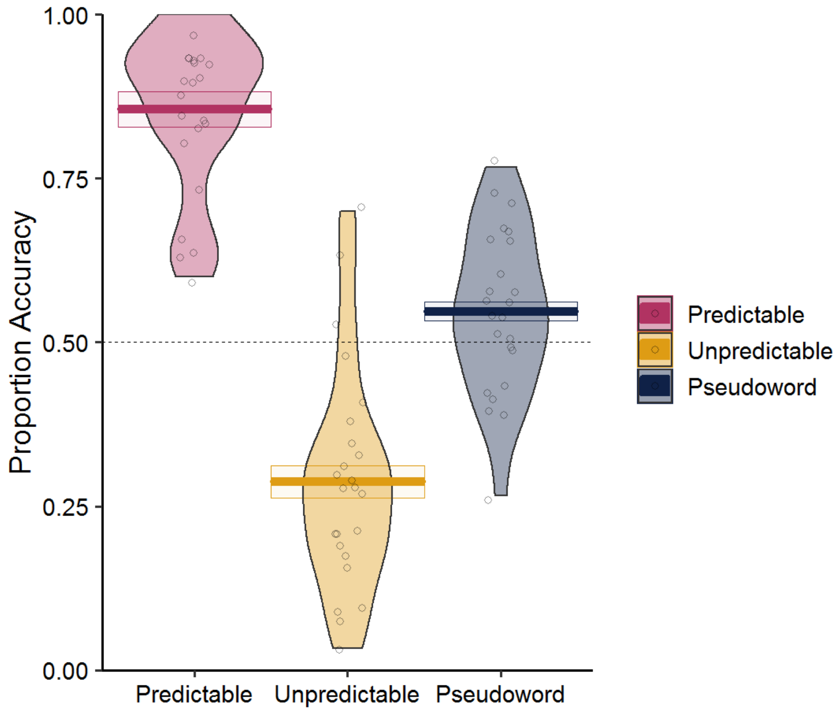

Figure 2. Mean accuracy rates for Experiment 2.

3.4.3 Discussion

The results show a dramatic effect of word predictability on letter identification. Readers identified letters with greater accuracy when the target was predictable from the sentence context. The odds of identifying the correct letter were over 16 times higher in predictable words compared to unpredictable words. Letter identification in unpredictable words was not only lower than in predictable words, but also lower than in pseudowords. This is particularly compelling considering the targets used in the unpredictable and pseudoword conditions were the same targets that demonstrated a word superiority effect when presented in isolation in Experiment 1. Further, letter identification in unpredictable words was not only lower than all other conditions, but significantly below chance. Predictability exerted a powerful influence over sub-lexical processing, as the word superiority effect was amplified in predictable words, and abolished in unpredictable words. In summary, predictability *facilitated* letter identification accuracy in predictable words and *inhibited* letter identification in unpredictable words relative to pseudowords.

These results cannot be understood within single word models of reading. Any real word is arguably more predictable than a pseudoword, even when it is unlikely to occur within a particular sentence context. Further, unpredictable words can still receive activation from word level representations whereas pseudowords cannot. In contrast, the results can be explained when pre-activation, competition effects and thresholding due to sentence context are taken into account. In the case of unpredictable words, the results suggest that readers selected the foil letter based on a good enough match to word level expectations.

It is important to address a potential limitation in the task methodology, as participants received no signal that selecting a letter based on predictability did not guarantee a correct response. Despite the careful wording of task instructions, there is a possibility that participants ignored the target and made letter-choice judgements solely based on preceding sentence context where possible. Participants did not receive feedback on the accuracy of their responses; thus, there was potential for participants to complete the task without being aware that this was an unreliable strategy. The fact that accuracy in the pseudoword condition was above chance provides evidence against this possibility. Nevertheless, we addressed this potential limitation by conducting a follow-up experiment to investigate whether the outcomes changed when participants received feedback on the accuracy of their responses.

3.5 Experiment 3

In Experiment 3, participants received feedback on their accuracy at the end of each trial to draw attention to the fact that word predictability cues were sometimes in conflict with precise letter information. This enabled us to address potential limitations in the design of Experiment 2 and observe whether readers adjust the weight of predictability cues based on feedback.

3.5.1 Method

3.5.1.1 Participants

This experiment included 24 participants (14 female, 10 male) from the same population as tested in Experiment 1. None of the participants were included in previous or subsequent experiments in this series.

3.5.1.2 Stimuli

Stimuli were identical to those used in Experiment 2.

3.5.1.3 Procedure and apparatus

The apparatus and procedure for Experiment 3 was the same as Experiment 2, except that participants received accuracy feedback immediately after each trial. The word “CORRECT” or “WRONG” appeared immediately after each button-press response for two seconds. Exposure duration for the target stimuli was determined for each participant using the same initial staircase-thresholding task as used in the previous experiments. Target exposure duration for the main experiment was 33 ms (two ticks) for 14 participants, 50 ms (three ticks) for five participants, 67 ms (four ticks) for three participants, 83 ms (five ticks) for one participant, and 100 ms (six ticks) for one participant.

3.5.2 Results

Accuracy data were modelled using a GLMM with the same fixed and random effect structure as Experiment 2. The data are visualised in Figure 3.

The results followed the same pattern observed for Experiment 2, although the differences and odds ratios between conditions were reduced. Accuracy was significantly higher for predictable word targets compared to unpredictable targets, $\beta = 1.64$, $OR = 5.15$, $SE = 0.12$, $Z = 13.62$, $p < .001$, and pseudoword targets, $\beta = 1.10$, $OR = 3.00$, $SE = 0.12$, $Z = 9.23$, $p < .001$. Accuracy rates were significantly lower for unpredictable targets relative to pseudoword targets, $\beta = -0.54$, $OR = 0.58$, $SE = 0.11$, $Z = -4.98$, $p < .001$.

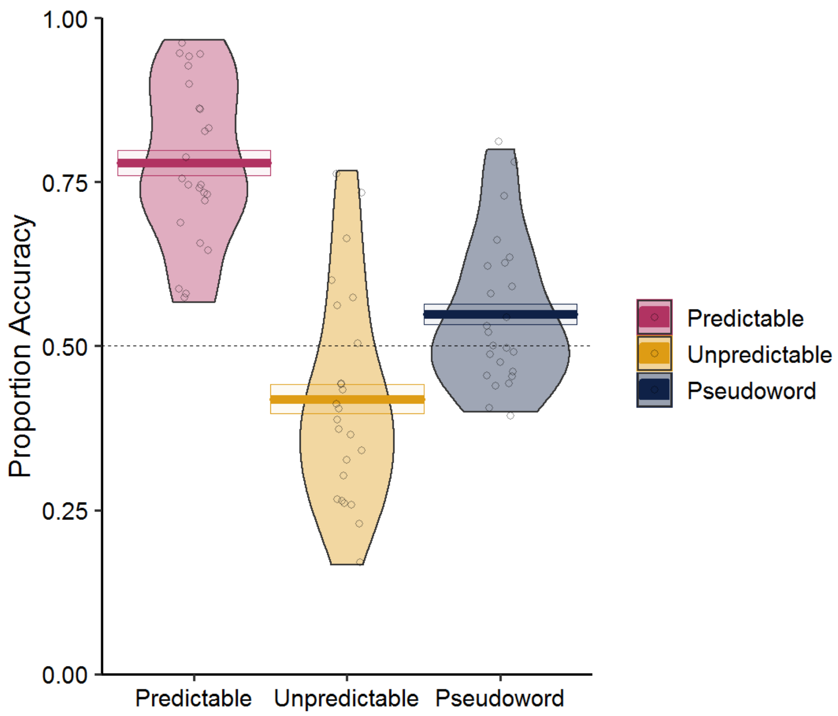

Figure 3. Mean accuracy rates for Experiment 3.

We compared Predictability effects across Experiments 2 and 3 by combining the data and including Feedback as a fixed effect. The model had the following structure: glmer(Accuracy ~ Predictability * Feedback + (1|Participant) + (1|Item) + (1|Exposure), family = binomial). The accuracy data showed a significant main effect of Feedback ($\beta = 0.54$, $OR = 1.72$, $SE = 0.16$, $Z = 3.33$, $p < .01$), as accuracy rates were significantly higher when participants received feedback after each response. The fit of the model improved when the interaction term was included ($\chi^2(2) = 40.52$, $p < 0.001$), which indicated an interaction between Feedback and Predictability.

3.5.3 Discussion

The pattern of results replicated those observed in Experiment 2. Once again, we observed the word superiority effect for predictable words, but not for unpredictable words. We also observed inhibition for unpredictable words, as accuracy was below pseudoword and chance performance. These findings address the methodological limitation identified in Experiment 2. It is unlikely that those results were obtained simply because participants were ignoring the targets because the same pattern is obtained when participants' attention is drawn to the accuracy of their decisions about those targets. Even with feedback, the word superiority effect was observed only when targets were predictable from sentence context. The word superiority effect was absent in the unpredictable condition, as the target did not align with the pre-activated representation, and the lower threshold adopted within the high contextual constraint environment hindered analysis of fine-grained letter information. Though feedback did not change the overall pattern of results, it did reduce the impact of predictability on the word superiority effect. We argue that feedback caused participants to increase the threshold for word recognition (thus permitting finer-grained orthographic processing). However, the fact that accuracy for unpredictable targets remained below chance highlights the very powerful influence of sentence context on letter identification.

The word superiority effect has been a cornerstone of our understanding of visual word recognition. Yet, findings across Experiments 1-3 demonstrate the fragility of this effect within sentence contexts. The exact same target stimuli were used in the word condition of Experiment 1 and the unpredictable condition in Experiments 2 and 3. The odds ratios demonstrate that, when these targets appeared in isolation, the odds of selecting the correct letter (compared to the foil letter) were 91% higher in the word condition than the odds in the pseudoword condition. However, when these words were unpredictable from sentence context, the odds of the participant selecting the correct letter (compared to the foil letter) were 42-68% *lower* than in the pseudoword condition. The findings indicate that the word superiority effect is not guaranteed, and that activation from word representations do not necessarily enhance letter identification.

In the next experiment, we sought to reinstate the word superiority effect by disrupting readers' ability to predict the target. Previous literature demonstrates that readers more readily recognise words in grammatical sentences compared to scrambled lists of the same words (Baddeley et al., 2009, Toyota, 2001). According to models of sentence reading, this word recognition advantage arises from predictability. When word order remains intact, readers are more able to predict an upcoming word and lower the evidence threshold to facilitate faster word recognition. When word order is disrupted, there is a recognition cost. Readers are unable to anticipate the upcoming word and therefore require a higher more stringent threshold to differentiate between word candidates, which results in longer recognition times. Higher thresholds reduce the speed of word recognition; however, they should provide an advantage for letter identification. We predict this because higher thresholds enable readers to process more precise letter information. As a result, disrupting word order within sentences may universally increase letter identification accuracy, despite reducing facilitation for word recognition.

Ultimately, disrupting readers' ability to predict the upcoming word is likely to reinstate the word superiority effect. Using a higher threshold enables readers to consult a much wider pool of word candidates to inform letter identification, and apply greater precision in differentiating between word neighbours. This prediction was tested in Experiment 4.

3.6 Experiment 4

In Experiment 4, we aimed to disrupt readers' predictions by jumbling the word order of the preceding sentence frames. We predicted that the difference in letter identification accuracy between predictable and unpredictable word targets would be smaller when sentence word order was disrupted, due to predictability exerting a lesser influence on word recognition. As result, letters in predictable words would receive less of a recognition benefit and letters in unpredictable words would receive a smaller recognition cost. We also expected letter identification accuracy to be universally higher in disrupted sentences, as disrupting predictability should increase readers' threshold of evidence for word identification. Consequently, we predicted that disrupted word order would elicit more precise letter identification processing, which should reinstate the word superiority effect.

3.6.1 Method

3.6.1.1 Participants

This experiment included 24 participants (19 female, 5 male) from the same population as tested in Experiment 1. None of the participants were included in previous or subsequent experiments in this series.

3.6.1.2 Stimuli

Stimuli were very similar to those used in Experiment 2. Target words and pseudowords followed the same highly predictable sentence frames; however, the words within the sentence frames were presented in a pre-randomized order (*landed the pilot the faulty calm plane/plate/plave*).

3.6.1.3 Procedure and apparatus

The procedure and apparatus were identical to previous experiments. Target stimuli exposure duration was 33 ms (two ticks) for 11 participants, 50 ms (three ticks) for 11 participants, and 67 ms (four ticks) for two participants.

3.6.2 Results

Accuracy data were modelled using a GLMM with the same fixed and random effect structure as Experiments 2 and 3. The data are visualised in Figure 4. Despite the disruption in word order, the results followed the same pattern observed for Experiments 2 and 3. Accuracy was significantly higher for predictable word targets compared to unpredictable targets, $\beta =$

0.96, *OR* = 2.61, *SE* = 0.12, *Z* = 7.82, *p* < .001, and pseudoword targets, β = 0.73, *OR* = 2.08, *SE* = 0.12, *Z* = 5.94, *p* < .001. Accuracy was significantly lower for unpredictable targets relative to pseudowords, β = -0.22, *OR* = 0.80, *SE* = 0.11, *Z* = -1.98, *p* = .047.

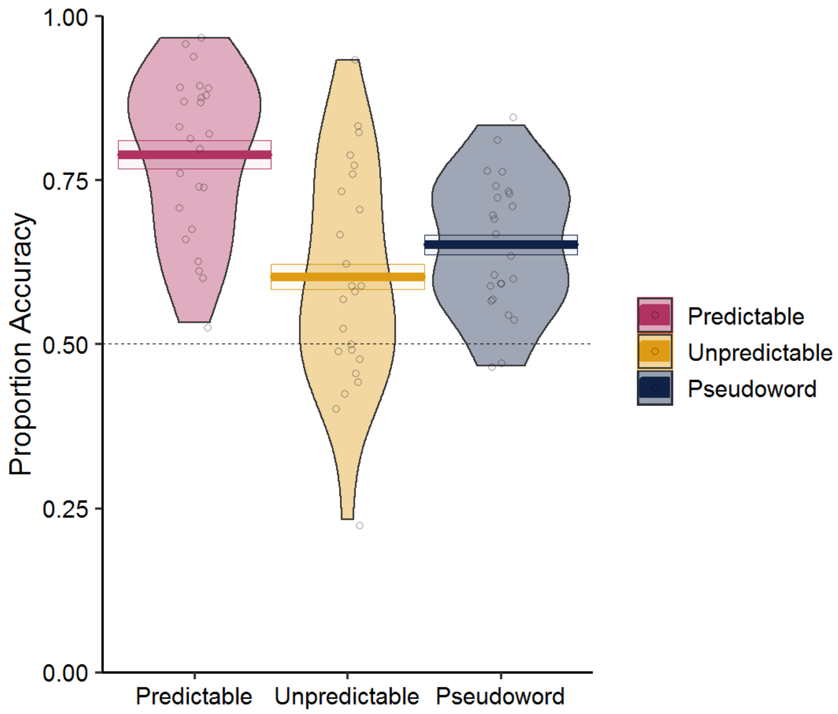

Figure 4. Mean accuracy rates for Experiment 4.

We compared the effect of word order across Experiments 2 and 4 by combining the data and including Word Order as a fixed effect. The model had the following structure: glmer(Accuracy ~ Predictability * Word Order + (1|Participant) + (1|Item) + (1|Exposure), family = binomial). The accuracy data showed a significant main effect of Word Order (β = -0.54, *OR* = 1.71, *SE* = 0.17, *Z* = -3.17, *p* < .01), as accuracy rates were significantly lower when the word order of the sentence was preserved. The fit of the accuracy model improved when the interaction term was included ($\chi^2(2)$ = 107.85, *p* < 0.001), which indicated an interaction between Word Order and Predictability. The interaction showed that letter identification accuracy in unpredictable words was significantly higher when the word order within sentence frames was disrupted.

3.6.3 Discussion

Predictability effects persisted even when sentence word order was disrupted, albeit with reduced effect. Predictable words yielded higher letter identification accuracy compared to unpredictable words and pseudowords, and accuracy rates for unpredictable words were still lower than for pseudowords. As observed in the previous experiments, the word superiority effect remained contingent on the word being predictable. Disrupting word order within sentence frames narrowed the gap in accuracy rates between conditions, which indicates that predictability exerted a lesser influence. However, this was not enough to reinstate the word superiority effect in unpredictable words.

Strikingly, overall letter identification accuracy was higher when sentence word order was disrupted rather than preserved. This finding is in the opposite direction to that observed in whole word recognition, in which word recognition accuracy is typically higher when sentence order is preserved. For example, Snell and Grainger (2017) reported that readers were more accurate at identifying words presented for a short 200 ms duration when they appeared in a grammatically valid sequence. We propose that, when sentence order is preserved, upcoming words are more predictable. In this situation, the reader can use a low threshold to increase the efficiency of word recognition. Consequently, precise letter processing is reduced as the reader accepts a good enough match to the pre-activated representation. However, disrupting word order within sentences reduces the predictability of the upcoming word. Therefore, the reader uses a higher threshold and pays closer attention to precise letter information. This introduces a cost for whole word recognition, but a benefit for letter identification.

According to models of sentence reading, word recognition thresholds are based on the cloze probability of the most likely word candidate. Disrupting word order within sentences is likely to drastically reduce this metric. To confirm, we conducted a post-hoc online sentence cloze task with the jumbled sentence frames to observe whether disrupting word order reduced cloze probability in a new sample of 42 participants. The mean cloze probability of the most common response was 0.31 (*SE*: 0.01), reduced from 0.79 when word order was preserved, ($t(89) = 18.79$, $p < .001$). These results confirm that disrupting word order significantly reduced the predictability of upcoming words.

Thus far, we have observed that the word superiority effect is only observed in sentence reading when the word aligns with readers' expectations. We argue that readers lower the threshold of evidence required for word recognition and deprioritize precise letter processing when targets are highly predictable. This leads to higher letter identification accuracy in predictable words that match cloze probability expectations, and lower letter identification accuracy in unpredictable words. Further, we have observed that cloze probability predictions *inhibit* letter identification in unpredictable words if the foil letter aligns with the expected word.

The previous experiments enabled us to compare letter identification in words with different cloze probabilities, or predictability from sentence context. In Experiments 1-3, we placed these words in contexts that strongly predicted one of the word targets. In Experiment 4, we disrupted sentence word order in order to reduce readers' ability to anticipate the upcoming target. However, we still observed greater letter identification accuracy in words with higher predictability. In the upcoming experiments, we instead manipulated contextual constraint, which refers to how many potential words are predicted from a sentence frame. Experiment 5 featured low constraint sentence frames that had many plausible forms of continuation (*the children were learning about…*). Experiment 6 featured high constraint sentence frames, which tended to predict a single word (*the rocket soared into outer …*). Across both of these experiments, words in each condition had low cloze probability and were equally as likely to occur.

Despite word targets having matched low predictability, we predicted different outcomes for the word superiority effect based on the preceding sentence context. We expected to observe the word superiority effect in sentences with many plausible forms of continuation (Experiment 5), as we predicted that readers would implement a higher evidence threshold in the absence of a predictable word candidate. Consequently, readers would consult a wider range of supporting word representations and engage in more precise letter processing in order to distinguish between them. This would enable them to differentiate between word neighbours within the Reicher-Wheeler task.

In contrast, we did not expect to observe the word superiority effect in sentence frames that predicted a single word (Experiment 6). We predicted that such contexts would evoke a low evidence threshold based on the high likelihood of a specific word occurring. As established earlier, a low evidence threshold is only beneficial for letter identification if the upcoming word aligns with the predicted representation. Otherwise, alternative word representations cannot support letter identification and the lower threshold means that readers are more likely to miss precise letter information required for distinguishing between word neighbours. Consequently, we did not expect to observe the word superiority effect as neither of our word targets aligned with the anticipated representation.

3.7 Experiment 5

The aim of Experiment 5 was to investigate letter identification in words placed low constraint contexts. We used the same word and pseudoword targets from the previous experiments, but re-assigned targets to new low constraint sentence frames, which allowed for many plausible forms of continuation (e.g. *the children were learning about…*). Both word targets had low cloze probability, and equal likelihood of occurring within the new sentence contexts.

We expected the word superiority effect to be restored across all word targets, despite their low cloze probability. If this were so, letters would be identified with greater accuracy in both word conditions compared to the pseudoword condition. We predicted that the word superiority effect would be consistently observed, as low constraint contexts would prompt readers to maintain a higher threshold of evidence required for word recognition, as the upcoming word could come from a large pool of candidates. In this case, readers would attempt to match the word to the closest known word representation, rather than a good-enough match to the anticipated representation. This would enable a broader range of word representations to support letter identification, meaning that the word superiority effect would be more widely observed across word targets. In addition, readers would engage in more precise letter processing which would provide an advantage for differentiating between word neighbours.

3.7.1 Method

3.7.1.1 Participants

This experiment included 24 participants (17 female, 7 male) from the same population as tested in Experiment 1. None of the participants were included in previous or subsequent experiments in this series.

3.7.1.2 Stimuli

Experiment 5 used the same targets as those used in Experiments 2-5. However, targets were assigned to new low constraint sentence frames, in which both target words had low cloze probability and were equally likely. The sentence frames used in Experiment 5 had the same properties as the sentence frames used in other experiments. Sentence frames consisted of seven words and 35-40 characters (e.g. *the boy admired the smooth white plane/plate/plave*).

We measured contextual constraint of the sentence frame and cloze probability of the targets by repeating the online sentence cloze task with the new sentence frames. A new sample consisting of 42 participants with the same characteristics as the previous experimental samples completed the task. Results demonstrated that sentences had low contextual constraint; on average the most common response for each sentence was provided on 0.12 (SE: 0.003) of occasions. Targets in the Predictable 1 condition (previously Predictable) had a mean cloze probability of 0.003 (SE: 0.001). Targets in the Predictable 2 condition (previously Unpredictable) had a mean cloze probability of 0.004 (SE: 0.001). There was no significant difference in cloze probability between the two conditions, $t(89) = -0.49$, $p = 0.623$.

3.7.1.3 Procedure and apparatus

The apparatus and procedure for Experiment 5 was the same as for Experiment 2. Target exposure duration was 33 ms (two ticks) for 12 participants, 50 ms (three ticks) for 10 participants, and 67 ms (four ticks) for two participants.

3.7.2 Results

Accuracy data were modelled using the same fixed and random effect structure as Experiments 2 through 4. The data are visualised in Figure 5. Accuracy did not significantly differ between the first and second group of word targets (Predictable 1 and Predictable 2), $\beta = 0.25$, $OR = 1.29$, $SE = 0.13$, $Z = 1.91$, $p = .056$. However, there was a significant difference between the pseudoword targets and the word targets in both conditions (Predictable 1: $\beta = 0.66$, $OR = 1.94$, $SE = 0.13$, $Z = 5.19$, $p < .001$, Predictable 2: $\beta = 0.41$, $OR = 1.51$, $SE = 0.12$, $Z = 3.33$, $p < .001$).

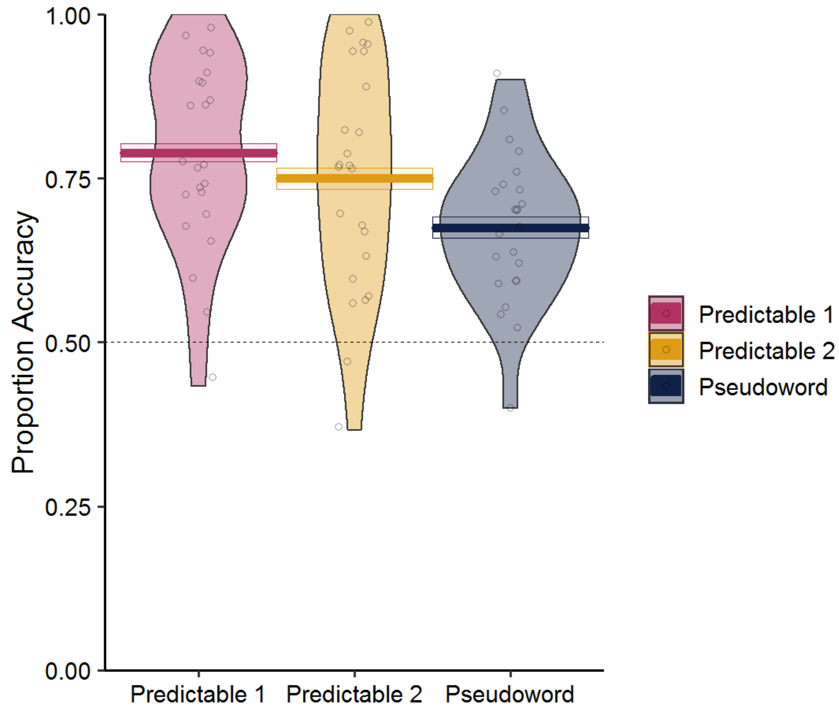

Figure 5. Mean accuracy rates for Experiment 5.

3.7.3 Discussion

In Experiment 5, the word superiority effect was restored in low constraint contexts. There was no difference in letter identification accuracy between word targets; however, accuracy was significantly higher in both word targets compared to pseudowords. These findings support the prediction that readers adapt their precision of sub-lexical processing based on contextual constraint. In low constraint contexts there is no single high cloze probability candidate, therefore participants maintain a high threshold and use precise sub-lexical processing to match the input to the closest known word representation. When the preceding sentence context does not narrow the pool of potential word candidates, readers use a similar degree of precision as when words appear in isolation. As a result, readers can distinguish between word neighbours and the word superiority effect is observed consistently.

Low constraint contexts prompt readers to use higher thresholds for word recognition that permit greater precision in letter processing. Readers rely upon the closest known word representation in the absence of a good-enough match; therefore letters that appear in any string with a corresponding word representation receive a recognition benefit. To confirm this interpretation, we used the final experiment to test the reverse. We placed low cloze probability targets in unlikely high constraint contexts in which readers were predicted to use a low threshold for word recognition.

3.8 Experiment 6

In Experiment 6, both sets of word targets had equally low cloze probability. Unlike the previous experiment, they were placed in high constraint contexts where an alternative high cloze probability word was predicted. We used the same high constraint sentence frames and targets as Experiments 2-3; however, targets were re-assigned to different sentence frames in order to make both word targets have equally low cloze probability.

We did not expect to observe a difference in letter identification accuracy across word targets, due to their equivalent unpredictability. In addition, we did not expect to observe a difference between words and pseudowords (as would be expected under the word superiority effect). We anticipated that high constraint contexts would pre-activate a single word candidate, which would inhibit other word representations and justify the use of a low threshold good-enough match to the expected word. For example, when reading "*the dog ran from the venomous…*" not only would readers not expect the final word to be *plane* or *plate*, they would strongly anticipate the word *snake*. Consequently, letter identification would only benefit from activation from word representations if the target matched the predicted pre-activated word representation. Our low cloze probability word targets should not receive this recognition benefit. Therefore, we did not expect to observe the word superiority effect in words with low cloze probability in high constraint contexts.

3.8.1 Method

3.8.1.1 Participants

This experiment included 24 participants (21 female, 3 male) from the same population as tested in Experiment 1. None of the participants were included in previous experiments in this series.

3.8.1.2 Stimuli

The stimuli used for Experiment 6 were the same as the stimuli used in Experiment 2. The 90 highly constrained sentence frames were randomly reassigned to targets, which resulted in each target within the triplet being unpredictable (*the dog ran from the venomous plane/plate/plave*).

3.8.1.3 Procedure and apparatus

The apparatus and procedure for Experiment 6 was the same as for Experiment 2. Target exposure duration was 33 ms (two ticks) for 15 participants, 50 ms (three ticks) for six participants, and 67 ms (four ticks) for three participants.

3.8.2 Results

Accuracy data were modelled using the same fixed and random effect structure as Experiments 2 through 5. Accuracy did not significantly differ between the two groups of word targets (Unpredictable 1 and Unpredictable 2), $\beta = 0.08$, $OR = 1.08$, $SE = 0.11$, $Z = 0.68$, $p = .499$. There was also no significant difference between pseudoword targets and either set of word targets (Unpredictable 1: $\beta = 0.20$, $OR = 1.22$, $SE = 0.11$, $Z = 1.74$, $p = .082$, Unpredictable 2: $\beta = 0.12$, $OR = 1.13$, $SE = 0.11$, $Z = 1.06$, $p = .287$. The data are visualised in Figure 6.

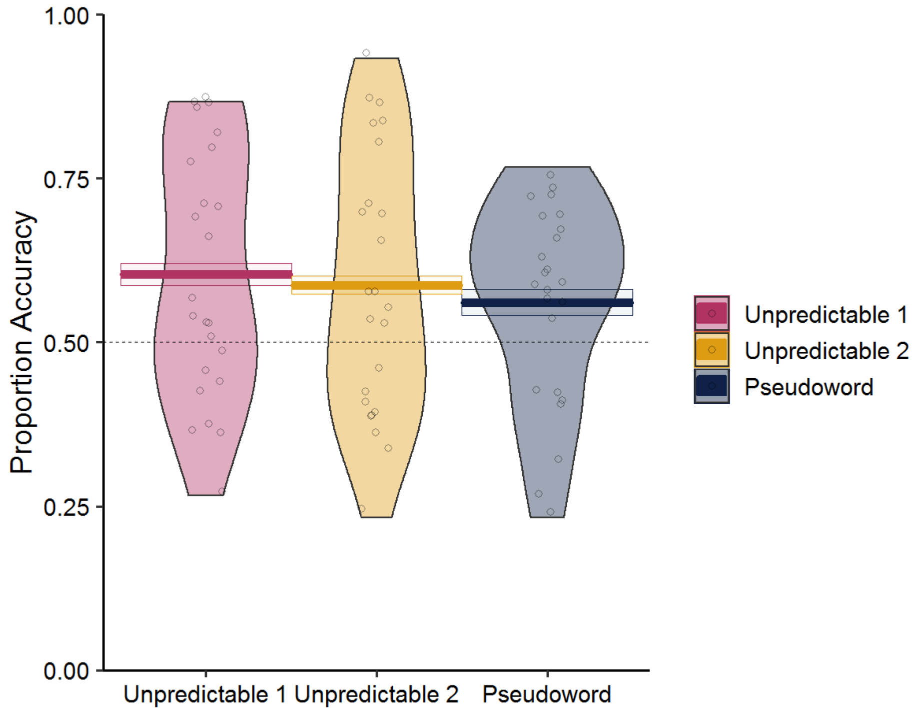

Figure 6. Mean accuracy rates for Experiment 6.

3.8.3 Discussion

As expected, there was no difference between targets in either of the word conditions and pseudoword targets. The word superiority effect was abolished. These findings further support our prediction that the word superiority effect is contingent on the word aligning with expectations from contextual constraint. When a high constraint context predicts a word with high cloze probability, readers expect to match the target to a specific pre-activated representation. As a result, readers use a less precise threshold to facilitate efficient word recognition. When the upcoming word does not meet cloze probability expectations, this lower threshold is costly. There is no support from corresponding word representations, because the pre-activated representation does not corroborate with the target. Readers are unprepared for an alternative word and the lower less precise threshold reduces the ability to distinguish between one letter different neighbours. This was first observed in Experiments 2 and 3. Experiment 6 demonstrates that this persists even in the absence of a foil letter that aligns with the cloze probability prediction.

In conjunction, Experiments 5 and 6 demonstrate that the precision of word recognition thresholds varies based on the contextual constraint of the sentence. When contextual constraint is high, readers rely on a good-enough match for efficient word processing. In the absence of predictability cues, such as in low constraint contexts, readers must pay more attention to precise letter information. More broadly, this indicates that letter identification is not encapsulated within word recognition. Processes that benefit word recognition do not necessarily benefit letter identification. In fact, our results demonstrate that thresholding aimed to facilitate efficient word recognition can introduce a cost for letter recognition.

3.9 General discussion

Our work demonstrates that the presence and nature of sentence context impacts substantially on letter identification. Previous evidence suggests that certain word representations are prioritised over others when a word can anticipated from sentence context (Asano & Yokosawa, 2011; Staub, 2015; Van Petten & Luka, 2012; DeLong et al., 2014), but very little attention has been given to how this influences sub-lexical processing.

We used the word superiority effect to explore whether word representations consistently support letter identification, or whether support from word representations is contingent on the word aligning with sentence level expectations. Participants identified letters in words and pseudowords, which appeared in different sentence contexts. Across six experiments, sentence frames varied in contextual constraint (the likelihood of accurately predicting the upcoming word) and word targets varied in cloze probability (the likelihood that a specific word would appear in the preceding sentence frame). The word superiority effect was not stable beyond single word context and fluctuated dramatically across experiments, despite targets remaining the same (Figure 7). These results indicate that the presence of a lexical representation does not provide a golden ticket to more efficient letter identification.

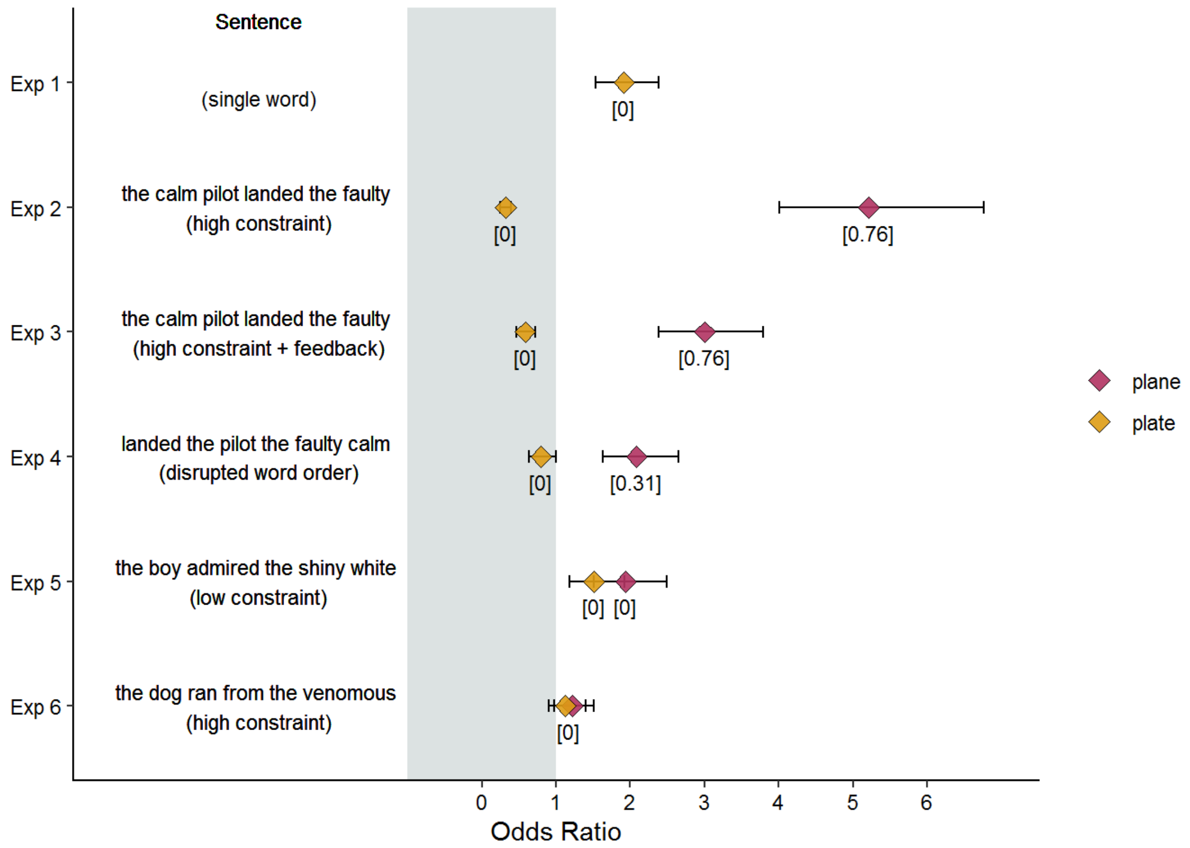

Figure 7. The odds ratio (*OR*) demonstrates the odds of correctly identifying the target letter (versus incorrectly identifying the foil letter) in a word compared to a pseudo-word. The colours refer to the same groups of word targets used across each experiment. If *OR* = 1.00, the odds of correctly identifying a letter are equal across words and pseudowords. *OR* > 1.00 (beyond the shaded box) indicates a word superiority effect. Bars display 95% confidence intervals. The cloze probability for each target condition is shown in brackets.

Our findings demonstrate that predictability not only provides a letter recognition advantage for predictable words, but also introduces a recognition cost when letters appear in words that do not align with expectations. In these cases, performance on unpredictable word targets was lower than that for pseudoword targets. This recognition cost for unexpected word targets was observed even despite the provision of feedback (Experiment 3) and despite jumbling word order to reduce participants' expectations (Experiment 4). These observations highlight the very powerful influence of sentence context on letter-level processing. We attribute this recognition cost to readers anticipating an alternative predictable word and, given the strong likelihood of this word occurring, misjudging the precision of sub-lexical processing required. Letter recognition suffers when the target word does not correspond with the expected word representation, and shallow sub-lexical processing hinders analysis of fine-grained letter information. These findings suggest that text comprehension processes may rely flexibly on a hierarchical set of cues. Readers rely preferentially on highly-constraining contextual information when it is available (hence abolishing the word superiority effect), but rely on lexical information when it is not available (hence reinstating the word superiority effect).

If highly-constraining sentence frames lead readers to adopt a lower word identification threshold, then the imprecise orthographic processing that results should also impair letter identification in pseudowords. Letter identification in pseudoword targets was above chance in all experiments, but it too was influenced by sentence context. Performance on pseudowords was worst in highly constraining sentences (55%, Experiment 2). Performance increased when word order disrupted predictability (65%, Experiment 4), and rose slightly further when pseudoword targets appeared in low constraint sentences (68%, Experiment 5). Performance was highest in Experiment 1 when pseudowords appeared in isolation (74%). These effects seem counterintuitive because informative sentence context might usually be thought to *enhance* processing. Yet, this pattern of data is consistent with the notion that participants adopted a lower threshold for word identification (resulting in lower orthographic precision) when contextual constraint was high. One question is why letter identification in pseudowords was reliably higher than in unpredictable words in high constraint contexts. We attribute this simply to the fact that in the latter case the foil letter corresponded to the predicted target.

Decades of research have informed computational models that aim to explain how we read words in isolation (McClelland & Rumelhart, 1981; Grainger & Jacobs, 1996) and in sentences (Reichle et al., 2003; Engbert et al. 2002; Engbert et al. 2005; Snell et al., 2018). However, our findings are difficult to interpret within these established models. Models that deal with letter identification focus on words presented in isolation (McClelland & Rumelhart, 1981; Grainger & Jacobs, 1996), and have nothing to say about how letter identification might vary based on sentence context. Conversely, models of sentence reading, which do consider context, avoid sub-lexical processes described by models of single word recognition. Whole words are the largest unit for models of single word reading and the smallest unit for models of sentence reading. There is very little crossover between the two. This theoretical gap would not be an issue if a model of single word reading could simply be added to a model of sentence reading to account for downstream letter identification processes. However, it would appear that it is not as simple as integrating the two, or assuming that one line of work can continue where the other ends. The dramatic shift that we observed across sentence frames (Figure 7) suggests that an additive model of this nature would be unsuccessful.

Currently, the OB1-Reader is the only known model to incorporate word recognition within sentence context and consider letter-level processing.[4] The model includes a word recognition module where letter information within the visual field activates lexical candidates. However, the sub-lexical processes of the OB1-Reader were developed to integrate a letter-

[4] The Glenmore model (Reilly & Radach, 2006) is also a sentence reading model that considers letter level processing. However, as Snell et al. (2018) note, sub-lexical processing is assumed a priori rather than modelled. Therefore, we are unable to directly interpret how the Glenmore model could account for our findings.

position coding scheme, as word nodes are activated through open bigram nodes. The model does not provide an explanation for how letters are *identified*, and as such, it cannot explicitly account for why readers are more accurate at identifying letters in words, subject to whether the word aligns with sentence expectations. One possibility is that an expected word candidate pre-activates specific word representations, and readers make a thresholded judgement based on bigram alignment. For example, in a high constraint sentence such as "*the calm pilot landed the faulty…*", orthographic neighbours "*plate*" and "*plane*" would share many of the same bigrams (*PL, PA, PE, LA, LE, AE*). Based on this, we may predict that the reader makes a rapid thresholded judgement on whether the bigrams are a good enough match with the expected word. As a result, letters in predictable words would receive a recognition benefit, whilst letters in unpredictable words (particularly in the case of orthographic neighbours) would receive a recognition cost. As a side note, if this were the case then we would also expect to see a letter identification cost in transposed-letter neighbours of predictable targets. In summary, the OB-1 Reader is the closest candidate with the potential to explain our results, as it is able to outline how graded word recognition in sentences and sub-lexical processing can be integrated. Whilst sub-lexical processing is currently focused on letter position coding, there is scope for how such processes could be applied to explain letter identification.

There are necessary limitations to the current work, which could be addressed with future study. Our paradigm used rapid serial visual presentation (RSVP), which is not naturalistic of sentence reading. Presenting the words in the sentence frame one word at a time enabled us to make the distribution of attention and fixation more consistent across participants. However, this presentation format also limited readers' ability to use processes often demonstrated in the eye-tracking literature, such as skipping and regressive saccades (Staub, 2015). It is also important to note that most sentence reading models, including the E-Z Reader, SWIFT and OB-1 models, assume that the reader is able to see the entire sentence. The E-Z Reader proposes that the reader uses parafoveal preview of an upcoming word to make a thresholded match of the input and the expected representation, whereas the SWIFT and OB-1 models assume parallel processing where readers process multiple words at once. The fact that predictability effects persisted in the absence of parafoveal preview or parallel word processing suggests that these processes are not absolutely necessary for predictability effects. It may be that our effects are reduced compared to what we would find with multiple word preview. One solution to this would be to conduct a similar study where the entire sentence frame is visible prior to the target. A previous study by Jordan and Thomas (2002) found similar predictability effects on letter identification when all words in the preceding sentence frame have been visible at the same time. They used popular phrases and found that letter identification accuracy was greater in the congruent word (*born to be wild*) compared to the incongruent neighbour (*born to be mild*).

The current work has demonstrated robust effects of word predictability on letter identification, and our manipulations demonstrate how different aspects of the word target and the sentence context can be systematically modified to measure the weighting given to various predictability and letter level cues. This series of experiments has demonstrated systematic consequences of manipulating cloze probability and contextual constraint under a short word recognition timeframe in a tightly controlled paradigm. Future work could test the fragility of such effects by changing the reading environment, and investigating whether this changes how various sub-lexical and contextual cues are hierarchically integrated. For example, empirical studies could test whether greater priority is given to letter level processing when the target exposure duration is lengthened, or whether predictability effects wane when the forward mask is extended. There may also be scope for investigating other contexts where predictability cues are in conflict. For example, in high constraint sentences where word targets that are orthographically similar have equally high cloze probability (e.g. *the dog was afraid of the bark/bath*). Corpus analysis could also provide insight on how often this is likely to occur in real-life context, or whether language distribution has evolved to prevent such occurrences from happening frequently.

3.10 Conclusion

The current work has considered how sentence context influences letter identification. The results demonstrate that readers do not assign the same weight to contextual and sub-lexical processing within each instance of word recognition. Letter identification processes are not consistent across or encapsulated within individual words, nor does the existence of a known corresponding word representation guarantee more accurate or efficient letter identification. Instead, priority assigned to precise letter processing depends on how accurately the whole word can be anticipated from sentence context. Cloze probability (the likelihood of a word occurring) and contextual constraint (the number of word candidates likely to occur) were established as key determinants of the precision of letter-level processing, and consequently, predictors of the word superiority effect occurring within various sentence contexts. These findings have critical implications for computational models, due to the theoretical gaps between models of sentence and single word reading. Sentence models are unable to explain sub-lexical processes such as letter identification, whilst single word models are unable to account for how the weight assigned to this processes will fluctuate based on surrounding context. These findings highlight the need for an integrated model that considers basic orthographic processes within meaningful sentence contexts.

CHAPTER FOUR: LETTER CONFUSABILITY ACROSS ORTHOGRAPHIC CONTEXTS

Investigating letter confusability from visual similarity across orthographic contexts

Lally, C. & Rastle, K. (in revision). Investigating letter confusability from visual similarity across orthographic contexts.

4.1 Abstract

Word recognition is facilitated by primes containing visually similar letters (*dentjst-dentist*, Marcet & Perea, 2017), suggesting that letter identities are encoded with initial uncertainty. Orthographic knowledge also guides letter identification, as readers are more accurate at identifying letters in words compared to pseudowords (Reicher, 1969; Wheeler, 1970). We investigated how higher-level orthographic knowledge and low-level visual feature analysis operate in combination during letter identification. We conducted a Reicher-Wheeler task to compare readers' ability to discriminate between visually similar and dissimilar letters across different orthographic contexts (words, pseudowords, and consonant strings). Orthographic context and visual similarity had independent effects on letter identification. In the absence of an interaction, we were unable to establish whether orthographic context mediates the effects of visual similarity specifically. However, we did find that higher-level orthographic information plays a greater role than lower-level visual feature information in letter identification. We propose that readers use orthographic knowledge to refine potential letter candidates while visual feature information is accumulated. This refinement may be essential in permitting the flexibility required to overcome within-letter feature variation whilst maintaining enough precision to tell visually similar letters apart.

All experiment materials, data, and analyses are available on the Open Science Framework: https://osf.io/p4q9u/?view_only=8485d54437b8473d92d1d50c37512fa0.

4.2 Introduction

Understanding the processes that underpin letter identification has been a long-standing goal within experimental psychology. Readers must maintain enough flexibility to recognise that *gate* and *GATE* are the same word, but also enough precision to recognise that *gate* and *gale* are not. Research shows that readers activate letter representations rapidly despite wide-ranging variability in their physical form (e.g. case and font; Bowers, et al., 1998; Hannagan et al., 2012; Kinoshita & Kaplan, 2008). However, existing literature also reveals that this flexibility extends beyond letter identity in the initial moments of word recognition. Masked priming paradigms demonstrate that word recognition is facilitated by prior presentation of stimuli that contain visually similar letters (*dentjst-DENTIST vs. dentgst-DENTIST,* Marcet & Perea, 2017*; document–DOCUMENT* vs. *docusnent–DOCUMENT*; Marcet & Perea, 2018), numbers (*C4BLE-cable* vs. *C9BLE-cable;* Kinoshita et al., 2013; Perea et al., 2008) or symbols (*C∆BLE-CABLE;* Perea et al., 2008). ERP data also demonstrate that strings containing letter-like numbers can facilitate lexical access, as such strings evoke similar N400 semantic responses to the words they resemble (*4PPL3-APPLE;* Lien et al., 2014). These findings suggest that the process of letter identification may consist of an accumulation of information about visual features.

Readers draw upon their knowledge of the writing system to support letter identification processes. For example, readers adjust prioritisation of different visual features as they gain expertise in an unfamiliar alphabet, in order to best discriminate between letters (Wiley et al., 2016). Letter identification is also guided by orthographic knowledge, such as knowledge of legal letter combinations or existing words. Consequently, the contexts in which letters appear can significantly alter readers' ability to discriminate between them. This principle is typically demonstrated using a Reicher-Wheeler task (Reicher, 1969; Wheeler, 1970), in which participants are briefly presented with a letter string, and then asked to decide which of two letters appeared in a specified position. Readers identify letters more accurately when they appear in a real word compared to a pseudoword (Coch & Mitra, 2010; Grainger & Jacobs, 1994; Kezilas et al., 2016; Reicher, 1969; Wheeler, 1970). This *word superiority effect* is understood as evidence that word representations enrich letter identification processes (Grainger & Jacobs, 1996; McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982). Letter identification is also more accurate in pronounceable pseudowords (*pable*) compared to unpronounceable consonant strings (*pkwtj*) (Baron & Thurston, 1973; Carr et al., 1978). This is described as the *pseudoword superiority effect.* This effect is proposed to arise from readers' knowledge of orthotactic constraints (i.e. restrictions on how letters combine within a writing system; Kezilas et al., 2016). The word and pseudoword superiority effects demonstrate that letter identification accuracy varies across contexts. Orthographic knowledge appears to play a key role in resolving early uncertainty around letter identity, and may reduce confusability from shared letter features. However, this line of research has not generally tested or controlled for effects of visual feature similarity.

Other work has investigated whether orthographic knowledge reduces the precision of visual feature information required for letter identification, by obscuring visual feature information and measuring readers' ability to overcome it. Studies have demonstrated that feature distortion is more disruptive in single letters (Fiset et al., 2008) and pseudowords (Rosa et al., 2016) compared to real words. Therefore, existing research indicates that readers use orthographic knowledge to resolve inconsistencies in visual feature information, whether it is distortion from visual noise (Fiset et al., 2008; Rosa et al., 2016) or substitution of a visually similar letter appearing in a word-like string (e.g. *dentjst*, Marcet & Perea, 2017). However, these scenarios typically involve readers encountering an invalid string and measuring how quickly they recover. Less is known about whether orthographic context reduces ambiguity from visual feature similarity if two letters are both valid. Readers often encounter this situation, as they must distinguish between word neighbours with similar looking letters (e.g. *gate-gale*). Based on previous findings, we would expect visually similar neighbours (*gate-gale)* to be harder to distinguish than visually dissimilar neighbours (*gate-game*). But how does letter confusability change across orthographic contexts? To our knowledge, researchers are yet to investigate whether orthographic context mediates readers' ability to discriminate between visually similar letters if they both result in a string with an equivalent word or non-word status.

Past work has shown that higher-level orthographic knowledge and low-level visual feature analysis both play a key role in letter identification, but less is known about how they interact. The visual forms of letters are highly variable; therefore, readers may use orthographic context to compensate for inconsistencies in visual feature information. For example, orthographic distributional knowledge provides information on how individual characters relate to each other by comparing the contexts in which they appear (Schubert et al., 2020). This knowledge can reinforce mappings between variable letter shapes and identities, provide cues on the expected visual form (such as case and font), and assist in refining potential letter candidates while visual feature information is still being accumulated. These orthographic context cues not only assist readers in overcoming within-letter visual variability, but also reduce the likelihood of confusing visually similar letters. For example, the letters *o* and *c* share many visual features, but may be less confusable in a word like *flow*, as competitor *c* would be de-prioritised for failure to comply with a known word or legal letter combination (*flcw*). Therefore, cues from orthographic context may play a role in constraining letter candidates in order to manage the balance of flexibility and precision required during letter identification. If so, letter confusability from visual similarity may be reduced when wider orthographic information is available, such as when letters appear in known words or legal letter combinations.

The focus of this work was to examine how higher-level orthographic knowledge and low-level visual feature analysis work in tandem during letter identification. We investigated whether the impact of visual feature similarity on letter confusability is mediated by orthographic context. We conducted a Reicher-Wheeler task to compare readers' ability to discriminate between letters with high and low visual feature similarity across words, pseudowords and consonant strings. We predicted that readers would be less accurate at discriminating between two letters with high visual feature overlap (*m-n*) relative to two letters with low visual overlap (*m-t*). We also predicted that letter identification would be more accurate in words relative to pseudowords, and pseudowords relative to unpronounceable consonant strings, in line with word and pseudoword superiority effects. Finally, we predicted that letter confusability from visual similarity would be reduced when letter-strings aligned with orthographic and orthotactic knowledge, as we proposed that readers use such knowledge to narrow down plausible letter candidates. Therefore, we predicted an interaction where accuracy differences between letters with high and low visual feature similarity would be smaller in words compared to pseudowords, and in pseudowords compared to consonant strings. Pre-registration, stimuli, data, and analysis scripts are openly available on the Open Science Framework.

4.3 Method

4.3.1 Participants

Seventy-two monolingual English speakers completed the experiment at Royal Holloway University of London, in exchange for £5. All participants were aged 18-35, with normal or corrected-to-normal vision, and no previous history of reading difficulty. The sample size was determined alongside the number of items (24 items per condition) in order to meet the suggested criterion of 1600 observations per condition for analyses using linear mixed-effects models (24 × 72 = 1728 observations per condition, Brysbaert & Stevens, 2018). All participants provided informed consent prior to taking part.

4.3.2 Stimuli

Target stimuli consisted of 48 words, 48 pronounceable pseudowords and 48 unpronounceable consonant strings. These three target stimuli conditions comprised the independent variable of orthographic context. Each target stimulus was assigned a target letter that was present within the stimulus, and two possible foil letters that were not present in the stimulus at all. Foil letters had either high visual feature overlap or low visual feature overlap with the target letter. Visual feature similarity (high versus low) was our second independent variable. The critical target and foil letters included in visual similarity comparisons were the same across each orthographic context condition. Substitution of the target letter with either of the foil letters always resulted in a string with the same orthographic context status as the target (e.g. word: *snow/show/stow,* pseudoword: *snum/shum/stum,* consonant string: *znsq/zhsq/ztsq*). All letter strings were four to six letters long, and words and pseudowords had a single-syllable pronunciation. Word targets (*snow*) and words with the substituted foil letter (*show/stow*) were controlled for frequency using the CELEX database (Baayen et al., 1995). Stimuli for a preliminary staircase-thresholding task consisted of an additional 20 words, 20 pseudowords and 20 consonant strings, with the same control measures as those used for the main task. None of the stimuli presented in the thresholding task were present in the main task.

Visual feature similarity was quantified using seven-point letter similarity ratings from over 700 people (Simpson et al., 2013). Target letters had a mean similarity rating of 4.19 with foil letters in the high overlap condition compared to 1.22 with foil letters in the low overlap condition, $t(47)=24.8$, $p<.001$. This difference between high- and low-overlap conditions was confirmed with a second, objective measure of visual similarity derived from the Hierarchical Model and X (HMAX, Mutch & Lowe, 2008), a biologically motivated computational model that mimics properties of the human ventral visual system through a series of simple (S1, S2) and complex (C1, C2) layers. We used HMAX S1 layer computations to calculate letter similarities, as this layer was modelled upon the earliest instance of feature detection. HMAX calculations revealed that target letters had a mean similarity rating of 0.59 with foil letters in the high overlap condition compared to 0.50 with foil letters in the low overlap condition, $t(47)=6.25$, $p<.001$. HMAX and reader ratings were positively correlated, $r(323)=.49$, $p<.001$.

4.3.3 Procedure

Participants completed a Reicher-Wheeler task consisting of 144 trials, administered using DMDX (Forster & Forster, 2003). Within each trial, participants viewed a 500 ms fixation cross, followed by a forward mask for 33 ms. A target letter-string (either a word, pseudoword or consonant string) then appeared for a predetermined duration (see below), before a hash symbol (#) backward-masked each letter of the target for 100 ms. During this time, a probe bar (|) appeared above and below one of the hash symbols, which indicated that the participant should identify the letter in the specified position. After 100 ms, a target letter and a foil letter replaced the probe bars above and below one of the hash symbols. The foil letter had either high visual feature similarity or low visual feature similarity to the target letter. Participants then had 5000 ms to make a button-press response to indicate which of the two letters was present within the string. Targets were counter-balanced to ensure that participants received an equal number of foil letters across high and low visual feature similarity conditions, and to ensure that participants saw each target letter-string once.

Target letter-string exposure duration was determined for each participant based on performance in an initial staircase-thresholding task (adapted from Davis, 2001), which used the same trial procedure and mask durations as the main task. In the thresholding task, target letter-string exposure duration began at 33 ms, and adjusted after each response. If the participant correctly identified the target letter, exposure duration was reduced by 17 ms (one tick). If the participant incorrectly identified the foil letter, exposure duration increased by 17 ms. Exposure duration was held constant after twelve changes in direction, and this value set target exposure duration for each participant in the main task. Exposure during the main experiment was 33 ms (two ticks) for 36 participants, 50 ms (three ticks) for 22 participants, 67 ms (four ticks) for 13 participants and 83 ms (five ticks) for one participant. The exposure durations were similar to previous Reicher-Wheeler studies with skilled adult readers (Chase & Tallal, 1990; Coch & Mitra, 2010; Grainger et al., 2003; Kezilas et al., 2016; Lété & Ducrot, 2008).

4.4 Results

Accuracy data were analysed using logistic generalized linear mixed-effects models with the *lme4* package (Version 1.1-12, Bates et al., 2015) in *R* (Version 4.0.4; R Core Team 2016). The maximal model was defined as: glmer(Accuracy ~ Visual Feature Similarity * Orthographic Context + (1|Participant) + (1|Item) + (1|Exposure Duration), family=binomial). The structure of the optimal model was determined using pairwise likelihood ratio tests (LRTs), in which random effects, main effects, and the interaction term were systematically added in turn. The model fit was improved by random effects of participant (LRT: $\chi^2(1)=293.77$, $p<.001$), item (LRT: $\chi^2(1)=553.77$, $p<.001$) and letter string exposure duration (LRT: $\chi^2(1)=11.44$, $p<.001$). The random effect of exposure duration referred to the duration each letter string was presented for, based on participant performance in the preliminary thresholding task. Although exposure duration was consistent within each participant, the intercept improved the fit of the model, which suggested that the random effect of exposure duration accounted for variance that could not be explained by the random effect of participant. Therefore, both random effects were included within the model. The fit of the model significantly improved when the fixed effects of visual feature similarity (LRT: $\chi^2(3)=32.70$, $p<.001$) and orthographic context (LRT: $\chi^2(4)=102.67$, $p<.001$) were included. However, the model fit did not improve when the interaction term was included (LRT: $\chi^2(2)=0.37$, $p=0.830$). This indicated that there was no significant interaction between visual feature similarity and orthographic context. Therefore, the final optimal model was structured as follows: glmer(Accuracy ~ Visual Feature Similarity + Orthographic Context + (1|Participant) + (1|Item) + (1|Exposure), family=binomial).

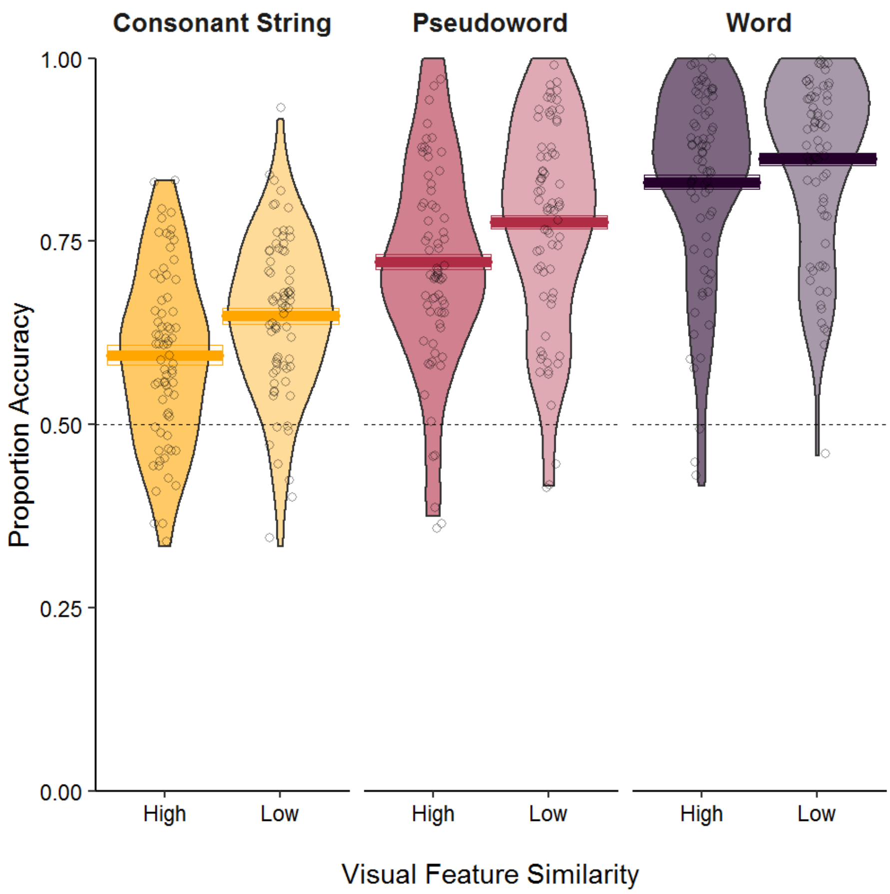

Figure 1. Mean accuracy rates for letter identification in the Reicher-Wheeler task. Crossbars display mean accuracy rates across participants and tiles display one standard error from the mean, calculated for within-subject designs (Loftus & Masson, 1994). Data points display accuracy rates for individual participants and violins demonstrate the distribution of the data. The dashed horizontal line displays chance performance.

Accuracy results are visualised in Figure 1. Beta (β) and odds ratios (OR) are used to report effect sizes. β is the logit transformed fixed effect coefficient, which refers to the estimated difference between conditions having controlled for random effects. OR (derived from β) measures the difference in odds of being correct (versus incorrect) in one level of a fixed effect compared to another. There was a main effect of visual feature similarity, as accuracy rates were significantly higher when the foil letter had low visual overlap with the target compared to when the foil letter had high visual overlap with the target, $\beta=0.27$, $OR=1.31$, $SE=0.05$, $Z=5.70$, $p<.001$. There was also a main effect of orthographic context. Accuracy rates were significantly higher for words compared to pseudowords, $\beta=0.67$, $OR=1.94$, $SE=0.11$, $Z=5.91$, $p<.001$, and consonant strings, $\beta=1.33$, $OR=3.78$, $SE=0.11$, $Z=11.94$, $p<.001$. Accuracy rates were also significantly higher for pseudowords compared to consonant strings, $\beta=0.66$, $OR=1.94$, $SE=0.11$, $Z=11.94$, $p<.001$.

4.5 Discussion

Our results revealed effects of orthographic context and visual feature similarity on letter discrimination in a Reicher-Wheeler task. Performance improved as letter strings became more word-like (words > pseudowords > consonant strings), replicating the word superiority effect and the pseudoword superiority effect (Baron & Thurston, 1973; Carr et al., 1978; Reicher, 1969; Wheeler, 1970). Performance was also superior when the discrimination involved letters with low visual similarity compared to letters with high visual similarity. There was no interaction between the effects of orthographic context and visual feature similarity; visually similar targets and foils were more confusable irrespective of how closely the visual input aligned with a real word. The odds ratios indicated that effects of orthographic context were much larger than effects of visual feature similarity. The large difference in effect sizes suggests that top-down orthographic knowledge may be relatively more important than bottom-up feature information in establishing letter identities.

We had predicted that low-level effects of visual feature similarity would be stronger where there is less higher-level orthographic information available. However, the interaction between orthographic context and visual feature similarity was not significant. Our interpretation of this null effect is limited, as despite having a relatively large sample size (*N*=72) and a repeated-measures design, our study was probably underpowered to detect this interaction (Brysbaert, 2019a). We ran Monte Carlo power analyses on simulated datasets to estimate the interaction effect sizes that could have been reliably detected with our sample size. Power analyses were conducted using the *simr* package (Version 1.0.5; Green & MacLeod, 2016) in *R* (Version 4.0.4; R Core Team 2016). We systematically increased hypothetical interaction effect sizes by $\beta = 0.05$ and ran 50 simulations for each increment, beginning at $\beta = 0.1$. For each simulation, we modelled a larger effect between words and consonant strings relative to words and pseudowords under our hypothesis that visual similarity effects would have a greater impact on letter identification when less orthographic information is available. Our sample size (*N*=72) yielded 80% power to detect an interaction with an effect size of $\beta = 0.3$ between visual similarity differences in words and pseudowords, and an effect size of $\beta = 0.4$ between visual similarity differences in words and consonant strings. These are typical *simple* effect sizes in psychology, but large *interaction* effect sizes. The equivalent odds ratios demonstrate that we had the power to detect an interaction if the benefit of having two visually distinct letters was at least 1.35 times more likely to improve letter discrimination in pseudowords relative to words, and 1.49 times more likely in consonant strings relative to words. These analyses suggest that, if there was an undetected interaction between visual similarity and orthographic context in our data, it was smaller than the effect sizes stated above. Power analyses and measures taken to protect against issues of post-hoc interpretation are reported in further detail on the Open Science Framework.

Despite power limitations, our investigation provided a new insight into how cues are weighted during letter identification. Notably, the influence of orthographic context was much larger than the influence of visual feature similarity. This suggests that top-down orthographic knowledge may be prioritised over bottom-up feature information during letter identification. We did not specify *a priori* predictions based on relative weighting of main effects; therefore, our interpretation is exploratory. This differential weighting may occur because orthographic knowledge plays a critical role in filtering letter candidates, enabling readers to maintain the balance of flexibility and precision required for letter identification. Readers must incorporate a certain degree of flexibility when mapping low-level visual features to letter identities, as the visual appearance of letters can be highly variable. However, allowing greater flexibility also increases the risk of letter confusability. We propose that orthographic knowledge mitigates this risk while visual feature information is still being accumulated, by disregarding unlikely letter candidates and prioritising those that would result in a real word or an orthotactically legal letter string. Even when multiple letters result in the same degree of word-likeness (as in our paradigm), cues from orthographic context still increase overall letter identification accuracy by reducing the number of potential letter candidates to discriminate between. Our findings provide evidence that *overall* letter confusability is reduced by orthographic context cues, which we attribute to readers disregarding unlikely letter candidates. This may be particularly beneficial if visually similar letters are de-prioritised, as they are typically more confusable. We originally predicted that this would manifest as an interaction, which we were unable confirm due to limited power. In the absence of a detectable interaction, this explanation remains speculative and we cannot confirm whether orthographic context mediates effects of visual similarity specifically. Further work with sufficient power to detect an interaction would be required to test this hypothesis with greater certainty.

4.6 Conclusion

The current study demonstrated that letter identification is supported through a balance of information from visual features and higher-level orthographic knowledge. Our results showed that visually similar letters are more confusable than dissimilar letters, indicating that readers initially encode letter identities with uncertainty, based on feature information. Word and pseudoword superiority effects demonstrated that readers use also use orthographic knowledge of known words and legal letter combinations to resolve early uncertainty around letter identity. We originally predicted that orthographic knowledge might reduce confusability from shared letter features. However, we did not find conclusive evidence to suggest that orthographic context mediates the effects of visual similarity specifically, as power limitations restricted our ability to detect an interaction. We did find that higher-level orthographic information plays a greater role than lower-level visual feature information in letter identification. We suggest that this is a result of readers using orthographic knowledge to refine potential letter candidates efficiently with while visual feature information is still being accumulated.

CHAPTER FIVE: ORTHOGRAPHIC CONSTRAINTS ON LETTER POSITION CODING

Shaping the precision of letter position coding by varying properties of a writing system

Lally, C., Taylor, J.S.H., Lee, C.H. & Rastle, K. (2019). Shaping the precision of letter position coding by varying properties of a writing system. *Language, Cognition & Neuroscience*, *35*(3). doi: https://doi.org/10.1080/23273798.2019.1663222.

CHAPTER 5: ORTHOGRAPHIC CONSTRAINTS ON LETTER POSITION CODING

5.1 Abstract

There is substantial debate around the nature of letter position coding in reading. Research on a variety of Indo-European languages suggests uncertainty in position coding; for example, readers perceive transposed-letter stimuli (jugde) as similar to their base words (judge). However, these effects are not apparent for all languages. We developed a powerful new method to delineate how specific properties of a writing system shape the representation of letter position. Two groups of 24 adults learned to read novel words printed in artificial scripts. One group learned a dense orthography (i.e. with many anagrams) and one group learned a sparse orthography (i.e. no anagrams). Following four days of training, participants showed a larger transposed-letter effect in the sparse orthography than in the dense orthography. These results challenge existing models of orthographic processing in reading, and support the claim that orthographic representations are shaped by the nature of the writing system.

All experiment materials, data, and analyses are available on the Open Science Framework: https://osf.io/g74vp/.

5.2 Introduction

There is a broad consensus that printed words in alphabetic languages are recognized through the analysis of letters. Information about letter identity helps readers to distinguish words like SLAT and SPAT that differ by a single letter, while information about letter position permits readers to distinguish anagrams like SLAT and SALT that consist of the same letters in different positions. The nature of position coding in visual word recognition has become a point of major theoretical debate over the past decade (e.g. Davis, 2010; Grainger & Whitney, 2004; Gomez et al., 2008).

Substantial evidence suggests that readers of Indo-European languages are tolerant of transposed letters in word identification (e.g., *jugde* activates *judge*; Perea & Lupker, 2003). In standard visual lexical decision, nonwords that are transposed-letter anagrams of words (e.g. silimar) are harder to reject than nonwords that are not (e.g. sitinar; Andrews, 1996; Chambers, 1979; Lupker et al., 2008; Perea & Lupker, 2004). Similarly, masked priming studies show that recognition of a target word is speeded by prior presentation of a transposed-letter prime (e.g. sevrice-SERVICE), relative to a substitution prime (e.g. sedlice-SERVICE; Schoonbaert & Grainger, 2004). This *transposed-letter effect* extends to cases in which the transposition crosses a syllable boundary (e.g. caniso-CASINO versus caviro-CASINO; Perea & Lupker, 2003) and to more extreme modifications (e.g. snawdcih-SANDWICH versus skuvgpah-SANDWICH; Guerrera & Forster, 2008). These findings all suggest that there is a high degree of perceptual similarity between stimuli that comprise the same letters in different positions.

These results highlight a fundamental problem in word recognition. Clearly, we can distinguish *snawdcih* and *sandwich*, so letters must be coded for position. However, this coding must comprise some degree of uncertainty or flexibility; otherwise, these stimuli would not be treated as perceptually similar. This insight has inspired a variety of competing theories that propose to solve this problem, including the SOLAR model (Davis, 2010), the Open Bigram model (Grainger & Whitney, 2004), the Noisy Channel model (Norris & Kinoshita, 2012), and the Overlap model (Gomez et al., 2008). Though these models have important differences, they all assert that letter position is coded in a way that leads to perceptual uncertainty. Further, uncertainty in letter position coding is argued to be a general property of the cognitive system (Perea & Carreiras, 2012), and caused by low-level visual (e.g. crowding, acuity; Grainger et al., 2016) and neurobiological factors (e.g. noisy retinotopic firing, nature of the receptive field structure; e.g. Dehaene et al., 2005).

However, recent evidence suggests that letter position uncertainty does not extend to all writing systems. In a series of studies in Hebrew, Velan and Frost (2007, 2011) showed that word recognition is *not* facilitated by prior presentation of a transposed-letter prime relative to a substitution control. Frost (2012b) argued that the reason for this can be traced to properties of the writing system. Specifically, Hebrew is very dense orthographically, with many anagrams. Hebrew readers must therefore develop precise orthographic position coding, as tolerance to disruptions of letter order would often result in accessing the meaning of the wrong word. Evidence for precise orthographic representations has also been provided in Korean (Lee & Taft, 2011; Rastle et al., 2019) – another language with a dense orthography, but which otherwise shares little similarity with Hebrew. Frost (2012b) emphasized that reading is a learned skill, and that while this process will necessarily be constrained by low-level visual and neurobiological processes, flexibility will emerge only where it maximises the efficiency of word recognition. This conclusion is supported by simulations showing that distributed-connectionist networks trained on artificial languages yield more flexible position coding for sparse orthographies compared to dense orthographies (Lerner et al., 2014).

Though Frost (2012b) presents a compelling argument that orthographic density is a major constraint on letter-position coding, it is difficult to draw this conclusion definitively from cross-linguistic comparisons since there are substantial differences across languages over and above orthographic density. Hebrew is characterised by a non-concatenative morphological system comprising tri-consonantal roots, which modify properties of the verb such as person, gender and tense. Similarly, Korean is characterised by physically-demarcated syllable blocks with a rigid consonant-vowel-consonant structure. In addition, readers of these languages almost certainly differ in a myriad of ways (e.g. method of reading instruction, language and reading experience). In light of these differences, it is difficult to draw strong conclusions about the specific impact of density on the development of orthographic representations.

Our work brings a new dimension to this debate by using an innovative approach that has the potential to reveal how flexibility in position coding is influenced by specific properties of writing systems. We use a laboratory analogue of reading acquisition in which adults are trained on novel words in unfamiliar scripts (Taylor et al., 2011, 2017). This approach allows precise control over *what participants learn* and *how they learn* in a way that could never be achieved using natural language comparisons. We trained participants on novel words from artificial writing systems designed to be orthographically sparse or dense, but which otherwise were *identical* in factors relevant to word perception (e.g. syllable structure, morphological structure, positional letter frequency). We then used the transposed-letter effect to assess the precision of participants' emerging letter position coding. On the basis of Frost (2012b), we predicted that participants who had learned the orthographically dense writing system would show a smaller transposed-letter effect, indicating greater precision in letter position coding, than those trained on the sparse writing system.

5.3 Method

5.3.1 Participants

Forty-eight monolingual English speakers completed the experiment at Royal Holloway University of London, in exchange for £60. All participants were aged 18-25 years old and had no history of language or reading difficulties. Participants were assigned to one of the two writing systems.

5.3.2 Stimuli

5.3.2.1 Trained items

Two artificial writing systems were constructed, each comprising 24 pseudowords printed in an unfamiliar script. In both writing systems, each novel word consisted of five letters and two syllables, and had a CVCVC structure. These novel words were constructed from 17 letters (12 consonants, 5 vowels), and the spelling-to-sound relationship in both languages was consistent, i.e. each letter had one sound. Critically, both the overall frequency and positional frequency of individual symbols was equated across writing systems, with consonants appearing 6 times and vowels appearing 8-10 times in the trained novel words. However, one writing system was sparse (i.e. no anagrams) while the other writing system was dense (i.e. each word was an anagram of another word in the orthography, created by switching the initial and final consonant or by switching the initial and middle consonant). Figure 1 presents an example of the trained stimuli from the sparse and dense writing systems and their pronunciations.

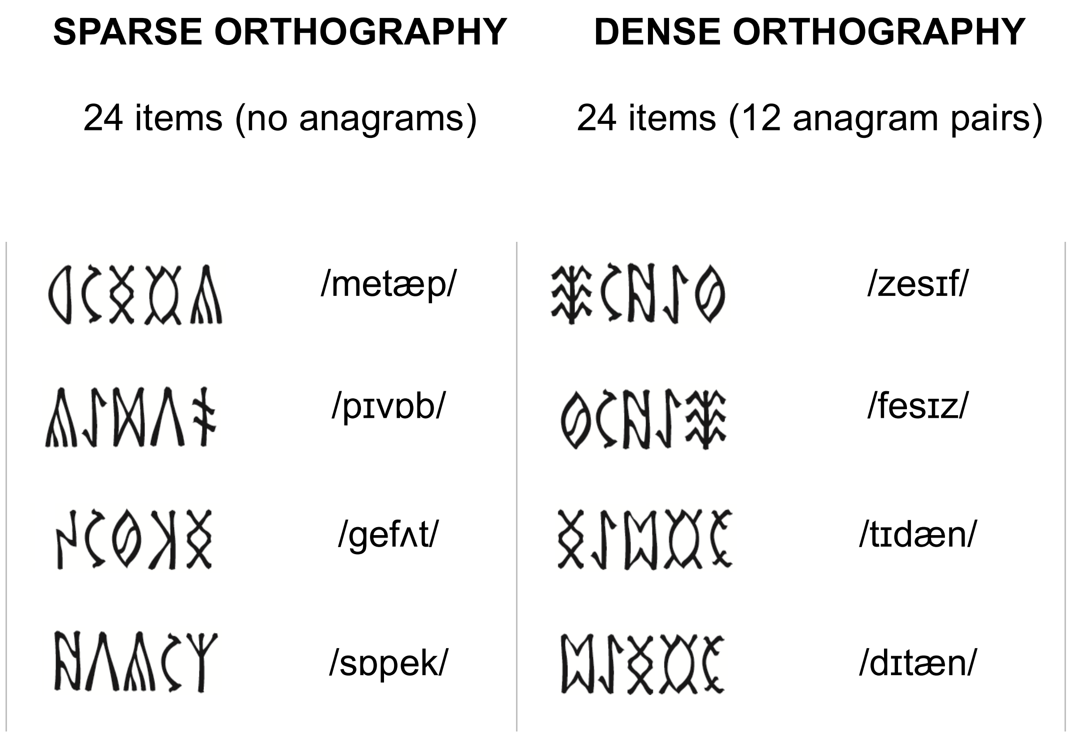

Figure 1. Examples of stimuli in dense and sparse orthographies.

5.3.2.2 Test items

In addition to the trained items, test tasks (conducted on the fifth day) required development of five sets of 24 untrained novel words for each writing system. Untrained words all comprised the same CVCVC structure as trained words, and each set was group-wise matched to trained words on letter frequency. The first four sets of untrained words were created for the visual lexical decision test task. The first set comprised novel words that transposed the second and third consonants of a trained word (TL-C), while the second set comprised novel words that replaced the second and third consonants of a trained word with different consonants from the alphabet (RL-C). The third set comprised novel words that transposed the first and second vowels of a trained word (TL-V), while the fourth set comprised novel words that replaced the first and second vowels with different vowels from the alphabet (RL-V).[5] The fifth set of untrained words was used to assess generalisation performance in reading aloud.

In designing the stimuli, we took great care to make sure that the similarity between test stimuli and trained stimuli was equivalent across sparse and dense orthographies. We used the Match Calculator (Davis, 1999) to assess the degree of similarity between trained and test items on a number of different input coding schemes. Each comparison generated a number between 0 and 1, where 0 indicated total dissimilarity and 1 indicated a perfect match. It is evident from the average match scores provided in Table 1 that there were no differences in trained–test item similarity across the two orthographies. This tight control was essential so that any differences in lexical decision performance could be attributed to orthographic density, rather than low-level differences in discrimination difficulty across sparse and dense orthographies as a result of higher orthographic overlap with trained and untrained items.

[5] We used non-adjacent transpositions of consonants and vowels for the reason that in our alphabets, the symbols associated with consonants and vowels only occur in certain positions (e.g. vowel symbols do not occur in the third position). We had no predictions about consonant-vowel status on the transposed-letter effect, and note that this comparison in any case is confounded with position of disrupted letters.

Table 1.

Match Calculator (Davis, 1999) statistics displaying mean orthographic overlap between trained and untrained items

Orthography	Absolute	SOLAR (Spatial Coding)	Overlap Open Bigram	SERIOL Open Bigram	Binary Open Bigram
Dense	0.13	0.19	0.04	0.04	0.04
Sparse	0.13	0.19	0.04	0.03	0.04

5.3.3 Procedure

Each participant was trained on the novel words from one writing system over four days and tested on the fifth day. The correct response was given as feedback on each trial for training tasks; no feedback was given on test tasks.

During Day 1, participants completed three tasks, with each task comprising three runs. The first task was phonic training. For two runs, participants were exposed to individual letters and their sounds and asked to repeat each sound aloud. In the third run, participants were presented with the letter and had to produce the sound. The second task was reading aloud; participants saw each novel word and were asked to read it aloud. The third task was orthographic search; participants heard a novel word and selected its visual form from a grid of all 24 novel words. During Days 2-4, participants completed three blocks of training each day. Blocks consisted of three repetitions of reading aloud and one repetition of orthographic search. Training on each day took approximately 75 minutes.

On the fifth day, participants completed four test tasks in a fixed order. These included tasks similar to the reading aloud and orthographic search tasks practiced in training; however, each stimulus was presented once per task, and participants received no feedback on the correct response. In addition, participants completed visual lexical decision and generalisation. In the lexical decision task, participants were presented with letter strings and asked to decide whether they were words that they had learned.[6] The letter strings included trained words, and the four sets of untrained novel words (TL-C, RL-C, TL-V, RL-V). Trained words were repeated four times, so that "yes" and "no" responses were balanced. Trained items were included as fillers in order to provide a correct "yes" response, and also to measure participants' overall recognition of trained items. Untrained items were included to measure the transposed letter effect (shown by the difference in performance for TL and RL foils), reflecting the degree of position uncertainty in each orthography. In the generalisation task, participants were asked to read the fifth set of untrained novel words aloud. This allowed us to assess the extent to which participants had extracted underlying spelling–sound regularities from training on the novel words.

5.4 Results

Data from one participant were removed from all analyses due to poor learning of the trained items (63% correct on reading aloud test; 49% correct on "yes" response in lexical decision test). Data were analysed using analyses of variance (ANOVA) on accuracy and

[6] We chose to investigate transposed letter phenomena using standard lexical decision rather than masked priming because we judged that this would be more suitable for use with an artificial orthography training paradigm. Though there is ample evidence that participants can discriminate trained from untrained stimuli in such paradigms (e.g. Taylor et al., 2017), we are unaware of any evidence suggesting that trained items would yield masked repetition priming effects.

response times (RTs), although we note that previous studies in which adults have learned to read in an artificial script have typically focused only on accuracy (e.g. Taylor et al., 2011, 2017). Spoken responses were hand-marked for accuracy and RT by a research assistant naïve to the purpose of the study using CheckVocal software (Protopapas, 2007). Analyses were conducted on by-subject (F1) and by-item (F2) means. Results were interpreted as significant when effects held across both F1 and F2 analyses. Data and analysis scripts are available in the OSF storage for this project.

5.4.1 Training data (Days 1-4)

5.4.1.1 Phonic training (Day 1)

The analysis of phonic training data considered performance in the third run of phonic training, and included Orthography (sparse vs dense) as a factor. The analysis of accuracy data revealed no difference between sparse (M = 0.47, SE = 0.04) and dense (M = 0.42, SE = 0.04) writing systems, $F_1(1, 45) = 0.62$, $p = 0.43$; $F_2(1, 32) = 0.71$, $p = 0.40$. Similarly, there was no difference in RTs between sparse (M = 2177 ms), and dense (M = 1957 ms) writing systems, $F_1(1, 45) = 1.37$, $p = 0.25$; $F_2(1, 32) = 1.76$, $p = 0.19$. These data provide confidence that there were no initial differences between the language groups on ability to learn the artificial alphabets.

5.4.1.2 Reading aloud (Days 1-4)

The analysis of reading aloud training data considered Orthography (sparse vs dense) and Day as factors. Figure 2 provides a visual representation of the data. For accuracy, there was a main effect of Day, $F_1(3, 135) = 212.53$, $p < .001$; $F_2(3, 138) = 1531.50$, $p < .001$, with performance becoming more accurate over time. Although Figure 2 suggests slightly higher accuracy for the dense group, neither the effect of Orthography, $F_1(1, 45) = 3.17$, $p = .08$; $F_2(1, 46) = 16.29$, $p < .001$, nor the interaction between Day and Orthography, $F_1(3, 135) = 0.98$, $p = .41$; $F_2(3, 138) = 6.14$, $p < .001$, was reliable across by-subject and by-item analyses. For RTs, there was a main effect of Day, $F_1(3, 135) = 150.42$, $p < .001$; $F_2(3, 138) = 881.99$, $p < .001$, with faster responses emerging over time. The RT data showed no effect of Orthography, $F_1(1, 45) = 0.24$, $p = .63$; $F_2(1, 46) = 3.53$, $p = .07$, and no interaction between Day and Orthography, $F_1(1, 135) = 0.28$, $p = .84$; $F_2(1, 138) = 5.09$, $p < .01$.

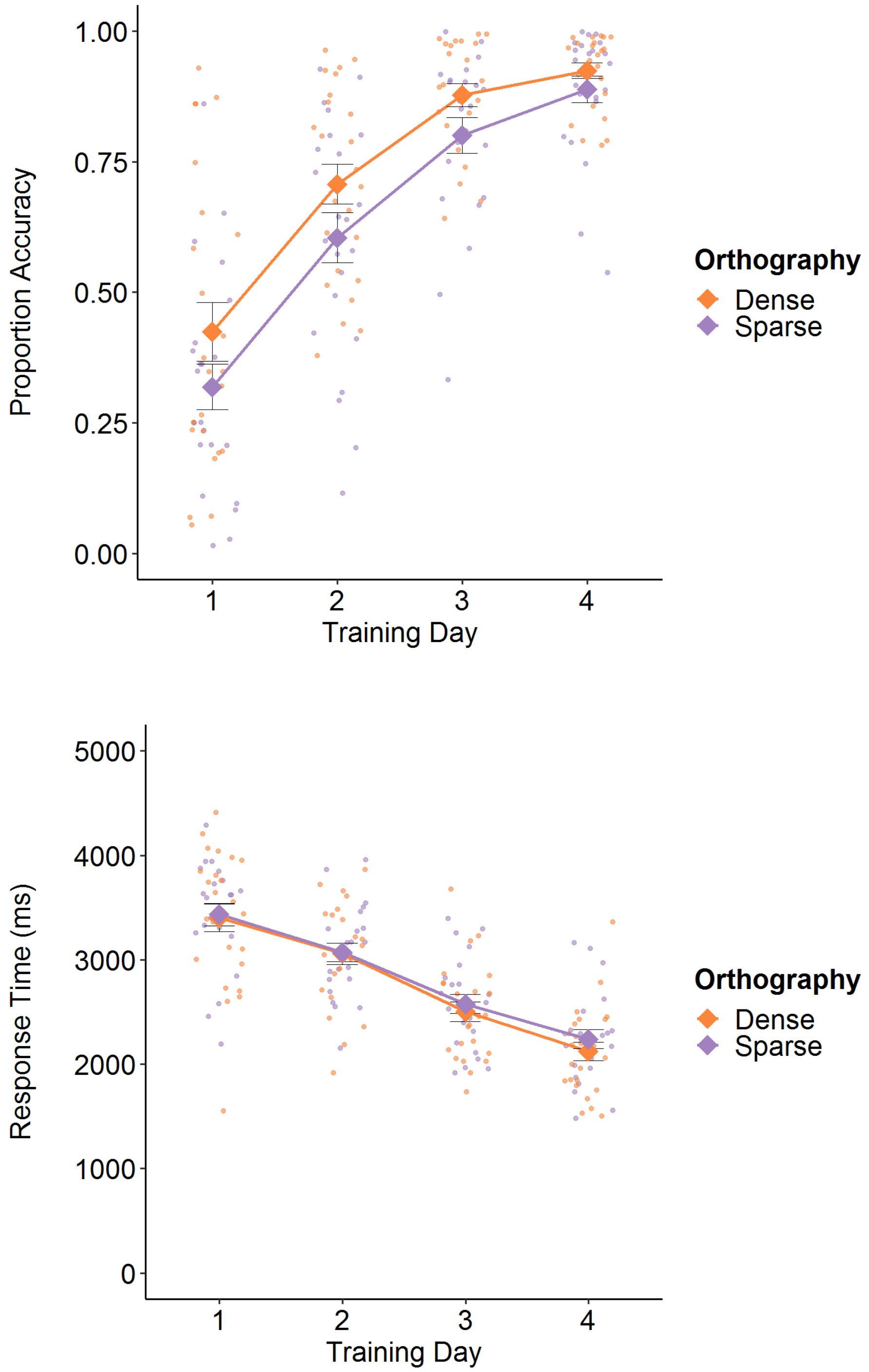

Figure 2. Mean accuracy and response times for each day of the reading aloud training task. Error bars display one standard error from the mean, calculated for between-subjects designs. Small data points display mean performance for individual participants. Data are averaged across three repetitions of the task on Day 1 and nine repetitions of the task on Days 2-4.

5.4.1.3 Orthographic search (Days 1-4)

The analysis of orthographic search training data considered Orthography (sparse vs dense) and Day as factors. Figure 3 provides a visual representation of the data. The accuracy analysis revealed an effect of Day, $F_1(3, 133) = 16.62$, $p < .001$; $F_2(3, 138) = 105.26$, $p < .001$, as accuracy increased over time. Although Figure 3 again suggests slightly higher accuracy for the dense group, there was no effect of Orthography, $F_1(1, 43) = 0.54$, $p = .47$; $F_2(1, 46) = 6.95$, $p < .05$, and no interaction between Day and Orthography, $F_1(3, 133) = 0.49$, $p = .69$; $F_2(1, 138) = 3.40$, $p < .05$, that was reliable across by-subject and by-item analyses. For RTs, there was a main effect of Day, $F_1(3, 133) = 100.50$, $p < .001$; $F_2(3, 138) = 391.89$, $p < .001$, as latencies decreased over time. The RT data showed no effect of Orthography, $F_1(1, 43) = 0.65$, $p = 0.43$; $F_2(1, 46) = 1.16$, $p = 0.29$, and no interaction between Day and Orthography, $F_1(3, 133) = 0.77$, $p = 0.51$; $F_2(3, 138) = 2.12$, $p = 0.10$. Overall, training data suggest that trained words were learned to a high degree of accuracy, with no reliable differences across sparse and dense orthographies.[7]

[7] We note that there was some indication from by-item analyses that the dense orthography may have been easier to learn for some of the participants (although performance converged by the end of training). This may suggest that there are meaningful individual differences in how these types of writing systems are learned. Future higher-powered studies may wish to investigate this possibility.

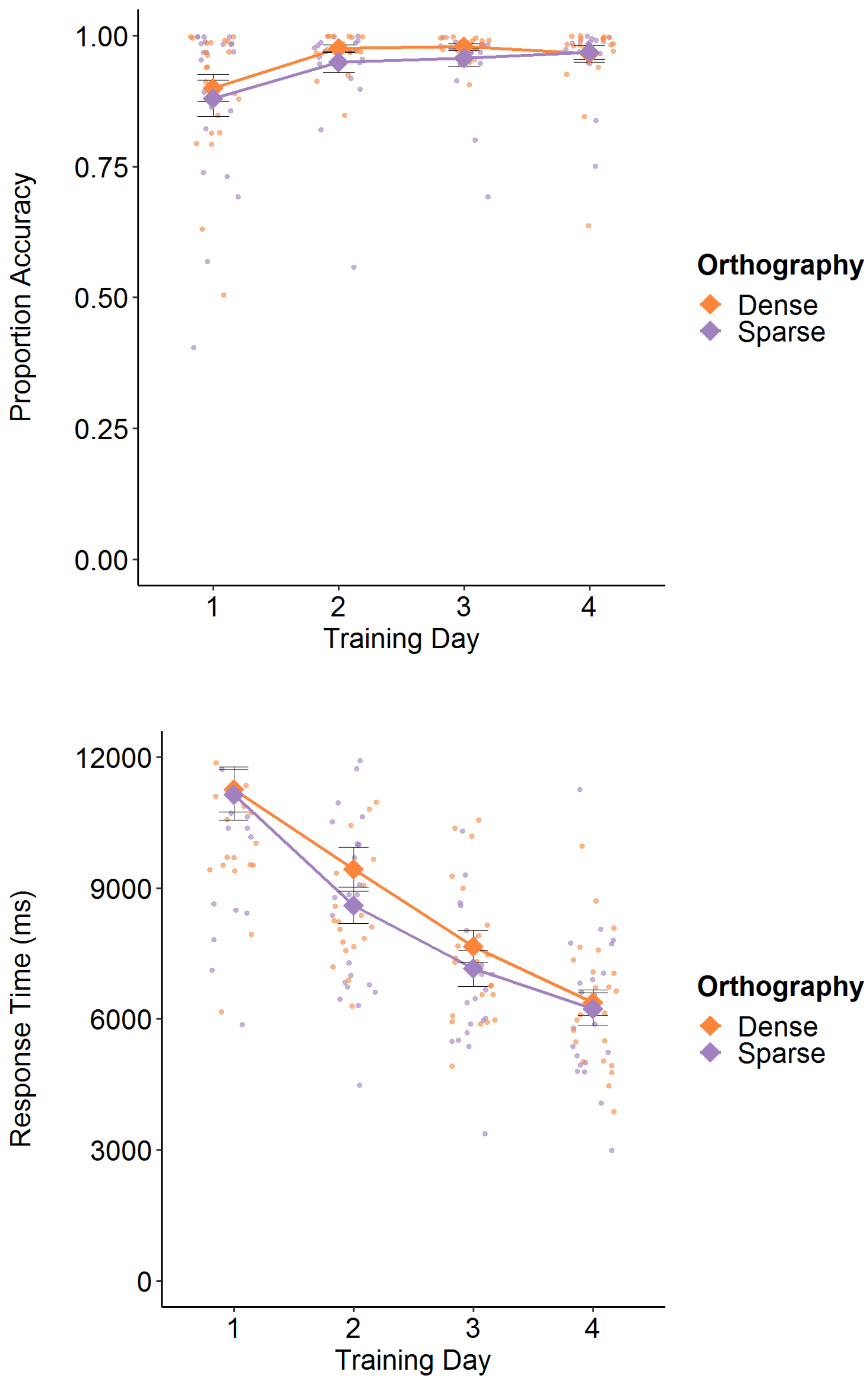

Figure 3. Mean accuracy and response times for each day of the orthographic search training task. Error bars display one standard error from the mean, calculated for between-subjects designs. Small data points display mean performance for individual participants. The data for each day are averaged across three repetitions.

5.4.2 Testing data (Day 5)

5.4.2.1 Reading aloud

The analysis of reading aloud test data included Orthography (sparse vs dense) and Lexical Status (trained vs untrained) as factors. Figure 4 provides a visual representation of the data. The analysis of accuracy revealed a significant effect of Lexical Status, $F_1(1, 45) = 139.97$, $p < .001$; $F_2(1, 92) = 450.67$, $p < .001$, with trained items read aloud more accurately than untrained items. There was also a significant effect of Orthography, $F_1(1, 45) = 12.17$, $p < .01$; $F_2(1, 92) = 50.96$, $p < .001$, with higher accuracy in the dense orthography. However, these main effects were qualified by an interaction, $F_1(1, 45) = 11.63$, $p < .01$; $F_2(1, 92) = 37.02$, $p < .001$. This interaction revealed that whilst performance on trained items did not differ as a function of Orthography, $F_1(1, 45) = 0.75$, $p = .39$; $F_2(1, 46) = 1.54$, $p = .22$, performance on untrained items was more accurate for the dense than the sparse orthography, $F_1(1, 45) = 13.19$, $p < .001$; $F_2(1, 46) = 53.32$, $p < .001$. The analysis of RT revealed an effect of Lexical Status, $F_1(1, 44) = 160.38$, $p < .001$, $F_2(1, 92) = 331.67$, $p < .001$, with longer latencies for untrained than trained items. However, there was no effect of Orthography, $F_1(1, 44) = 0.03$, $p = .87$; $F_2(1, 92) = 0.001$, $p = 0.98$, and no interaction between these factors, $F_1(1, 44) = 0.01$, $p = .94$; $F_2(1, 92) = 0.20$, $p = 0.66$.

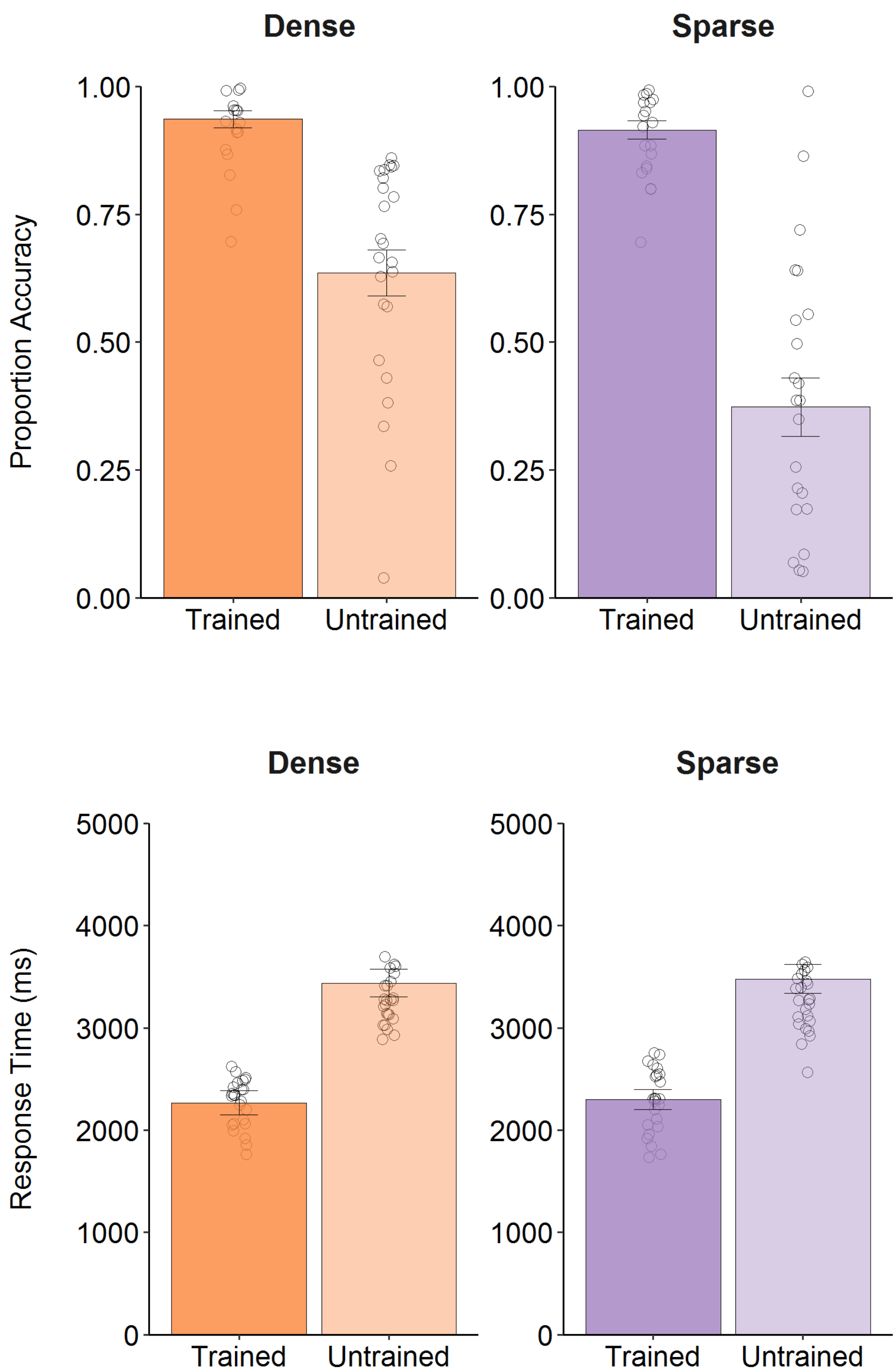

Figure 4. Mean accuracy and response times for reading aloud trained and untrained stimuli on Day 5. Error bars display one standard error from the mean, calculated for between-subjects designs. Data points display mean performance for individual participants.

5.4.2.2 Orthographic search

The analysis of orthographic search test data included Orthography (sparse vs dense) as a factor. The analysis of accuracy revealed no significant difference between sparse (M = 0.97, *SE* = 0.07) and dense (M = 0.98, *SE* = 0.05) orthographies, $F_1(1, 45) = 0.17$, $p = .69$; $F_2(1, 46) = 0.47$, $p = 0.50$). Similarly, the analysis of RT revealed no significant difference between sparse (M=6851) and dense (M=7131) orthographies, $F_1(1, 45) = 0.28$, $p = .60$; $F_2(1, 46) = 0.61$, $p = 0.44$.

5.4.2.3 Lexical decision

Analysis of the “YES” response included Orthography (sparse vs dense) as a factor. The analysis of accuracy revealed no difference in recognition of targets learned in sparse ($M = 0.95$, $SE = 0.01$) and dense ($M = 0.94$, $SE = 0.02$) orthographies, $F_1(1, 45) = 0.21$, $p = 0.65$; $F_2(1, 46) = 1.07$, $p = 0.31$. Similarly, the analysis of RT revealed no difference in the speed with which targets learned in sparse ($M = 3502$ ms) and dense ($M = 3635$ ms) orthographies were accepted, $F_1(1, 45) = 0.14$, $p = 0.72$; $F_2(1, 46) = 0.83$, $p = 0.37$. Analysis of the “NO” response included Orthography and TL status (TL vs RL) as factors. Figure 5 provides a visual representation of the data. The analysis of accuracy revealed an impact of TL status, with lower accuracy in rejecting TL foils than RL foils, $F_1(1, 45) = 50.29$, $p < .001$; $F_2(1, 46) = 31.29$, $p < .001$. There was also a main effect of Orthography, $F_1(1, 45) = 5.63$, $p < .05$; $F_2(1, 46) = 58.72$, $p < .001$, with accuracy in the dense orthography higher than in the sparse orthography. Critically, however, these main effects were qualified by a significant interaction, $F_1(1, 45) = 8.33$, $p < .01$; $F_2(1, 46) = 5.09$, $p < .05$, which indicated a larger TL effect in the sparse orthography than in the dense orthography. The analysis of RT revealed no effect of TL status,

$F_1(1, 45) = 8.11$, $p < .01$; $F_2(1, 46) = 3.32$, $p = .07$, no effect of Orthography, $F_1(1, 45) = 0.001$, $p = 0.98$; $F_2(1, 46) = 0.001$, $p = 0.99$, and no interaction between TL status and Orthography, $F_1(1, 45) = 0.41$, $p = 0.53$; $F_2(1, 46) = 0.09$, $p = 0.77$.

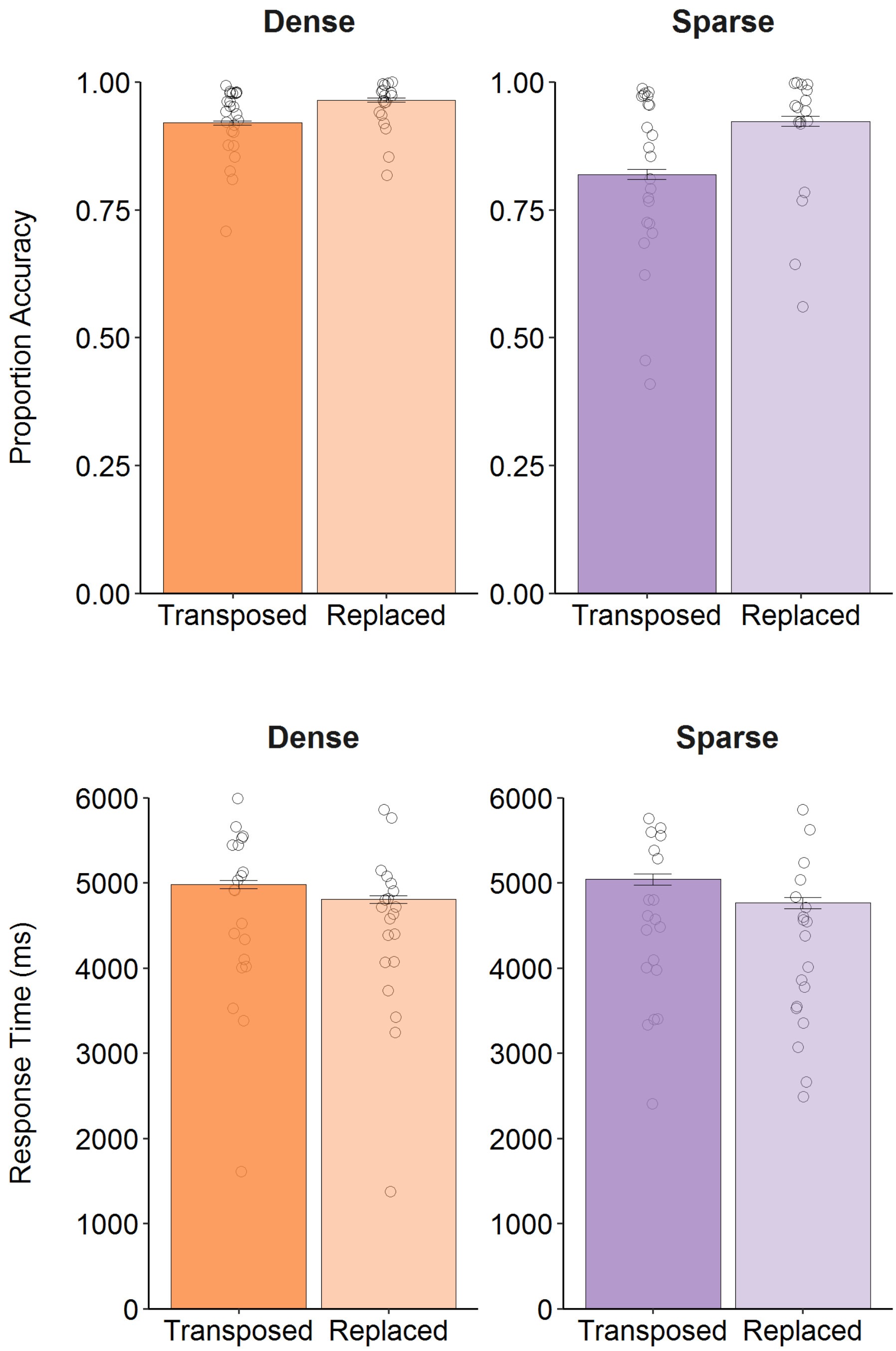

Figure 5. Mean accuracy and response times for the visual lexical decision test task on Day 5. Error bars display one standard error from the mean, calculated for within-subject designs (Loftus & Masson, 1994). Error bars display within-subject variability because the comparison of interest is the size of the transposed-letter effect within each orthography. Data points display mean performance for individual participants.

5.5 Discussion

Substantial research suggests that letter position is represented flexibly in skilled reading (e.g. Perea & Lupker, 2004; Schoonbaert & Grainger, 2004). However, recent research in Hebrew (Frost, 2012; Velan & Frost, 2011) and Korean (Rastle et al., 2019) suggests that this may not be a universal property of reading, but rather may depend on the orthographic density of a writing system. We sought to investigate the impact of orthographic density on the emergence of letter position coding using an artificial language learning paradigm. Over four days, participants learned to read novel words printed in an artificial orthography that was sparse (no anagrams) or dense (many anagrams). On the fifth day, they were tested in a variety of ways for their knowledge of the artificial orthographies. We assessed the precision of letter position coding through a lexical decision task, in which participants were required to accept trained words but to reject transposed-letter and replaced-letter foils. We took the size of the transposed-letter effect on rejection decisions as an index of flexibility in position coding (e.g. Andrews, 1996), and expected this to be larger in the sparse orthography than in the dense orthography.

Results revealed the predicted difference in the size of the transposed-letter effect on rejection decisions across sparse and dense orthographies. Though participants across the two writing systems learned trained words to the same high degree of accuracy, the underpinning orthographic representations clearly differed. Critically, participants who learned the sparse orthography were more likely to accept the transposed-letter foils as trained words (relative to a replaced-letter control) than participants who learned the dense orthography. This result indicates that participants' emerging orthographic representations were more precisely coded for letter position when they learned to read the dense orthography than the sparse orthography. We note that these findings arose on accuracy rather than RT. It is not surprising that findings should be confined to accuracy given the low level of experience that participants had with the novel alphabets. Indeed, the fact that “no” decisions in the lexical decision task hovered around 5000 ms suggests that reading of these alphabets was not fully automatized. The critical point is that there is no evidence of a speed-for-accuracy trade-off that would undermine the result on accuracy. If anything, the RT data go in the same direction as the accuracy data (i.e. larger transposed-letter effect in the sparse orthography).

These results are consistent with previous cross-linguistic studies demonstrating reductions in transposed-letter effects in orthographically-dense scripts such as Hebrew (Velan & Frost, 2007, 2011) and Korean (Lee & Taft, 2011; Rastle et al., 2019). However, our findings are particularly powerful because the impact of orthographic density on letter position coding cannot be attributed to other confounding language characteristics or to variations in participant groups across languages. These results support Frost’s (2012b) claim that the flexibility of letter position coding in reading arises as a consequence of the statistical structure of a writing system. However, a deeper question relates to how theories of reading acquisition might account for the impact of orthographic density on flexibility of letter position coding.

Several theories of reading acquisition highlight the linguistic environment as a key factor in forming optimal word representations. The amalgamation theory (Ehri & Wilce, 1980) and the lexical tuning hypothesis (Castles et al, 2001) both propose that readers develop more precise representations of words with a high neighbourhood density, due to the increased risk of confusability. This prediction has been supported in masked-priming studies showing that words in dense neighbourhoods show reduced substituted letter priming and transposed letter priming than words in sparser neighbourhoods (Castles et al., 2007; Forster et al., 1987; Kinoshita, Castles & Davis, 2009; Perea & Rosa, 2000). Our work suggests that the proposals of these theories regarding flexible tuning within a language might also be invoked to understand cross-linguistic differences. Readers of dense orthographies may require more precise tuning of word representations than readers of sparse orthographies, resulting in lower tolerance to transpositions.

Similarly, while our findings are inconsistent with the proposal that letter position flexibility arises solely as a result of low-level visual or neurobiological phenomena, we can envisage ways in which these theories might accommodate an influence of orthographic density. For example, the local combination detector model (Dehaene et al, 2005) proposes that detector sizes are larger for writing systems in which the reader is reliant on larger orthographic units (e.g. languages with low grapheme-phoneme transparency). This proposal offers a potential way forward for thinking about the impact of orthographic density on position flexibility, as in dense orthographies the reader may need to consider positional information from a larger window of letters in the word in order to reliably differentiate between anagrams.

However, we believe that the full range of the results observed are most compatible with the dual-pathway model of Grainger and Ziegler (2011). This model proposes that skilled readers use coarse- and fine-grained codes in parallel in order to decode written words. The coarse-grained route identifies letter combinations in the absence of precise positional information to provide a fast-track to semantic information. In contrast, the fine-grained route is more sensitive to the precise ordering of letters. The precision of orthographic information along the fine-grained pathway permits mapping onto phonological information as well as chunking of frequently-occurring contiguous letter combinations, such as morphemes. It seems plausible that during reading acquisition, learned representations of words are tuned to reflect an optimal balance of coarse-grained and fine-grained processing. If so, then readers of dense orthographies may be less able to utilise coarse-grained information, as the lack of position specificity would be inefficient for identifying words with many orthographic neighbours.

Rather, they would need to develop greater reliance on the fine-grained pathway. In contrast, readers of sparse orthographies with few orthographic neighbours would have more weight assigned to less precise representations as there is a much lower chance of identifying a transposed-letter neighbour in error. The reliance on less precise representations in orthographies with fewer orthographic neighbours would result in larger transposed-letter effects in sparse orthographies, as observed in the current work.

This account suggests that reading acquisition is characterised by a process of learning the degree of precision that is required for efficient word recognition. The optimal degree of precision may vary locally across different types of words, and may vary cross-linguistically based on orthographic density, as the present results suggest. This interpretation is supported by research suggesting that the magnitude of the transposed-letter effect *increases* through the period of reading acquisition (Ziegler et al., 2014 in French; Colombo et al., 2017 in Italian). This evidence stands in contrast to the predictions of the lexical quality hypothesis (Perfetti, 2007), stating that the process of reading acquisition is characterised by increased fine-tuning of representations (i.e. greater precision) through the accumulation of print experience.

One problem with this account based on the dual-pathway model (Grainger & Ziegler, 2011) is that seems to allow too many degrees of freedom. That is, one might argue that the model allows the researcher to explain any number of effects simply by suggesting *posthoc* that coarse-grained or fine-grained processing dominated. The account would be more persuasive if we had additional, independent evidence that participants in our dense orthography condition were more reliant on fine-grained processing. Remarkably, data from the generalisation test task provides this independent evidence. Results indicated that the trained words were learned to the same high degree of accuracy across writing systems. Yet, when participants were asked to read aloud untrained words using the same symbols, participants who learned the dense script showed a substantial advantage. This suggests that participants who learned the dense orthography developed more componential representations, reflecting greater fine-grained letter-to-sound knowledge, than participants who learned the sparse orthography. Once again, the evidence indicates that the nature of the writing system impacted on how the words were learned.

The introduction of the artificial orthography training paradigm has allowed us to study the unique impact of orthographic density on the acquisition of orthographic representations. Due to associations between orthographic density and other factors in existing writing systems, this type of highly-controlled study is only possible in a simulated environment. However, there are clearly limitations of these paradigms, introduced largely due to constraints on what participants are able to learn over a reasonable time period. Further, we have simplified our vocabularies in many ways to facilitate the learning task (e.g. use of a strict syllabic structure for all items), and to ensure perfect matching across orthographies. These simplifications may have had unintended consequences. For example, while participants across orthographies differed substantially in their treatment of *untrained* items in the lexical decision and reading aloud tasks, we observed no differences across orthographies in the speed or accuracy with which *trained* items were processed. We believe that the data from untrained items indicates that the writing systems were learned in different ways, but we would not like to speculate that writing system has no bearing on the speed or accuracy with which words are processed once learned. It may be that the null effect of orthography on the processing of trained items reflected the very tight, artificial matching across orthographies, or that our tasks were insufficiently sensitive to detect effects on trained items (see also Footnote 3). These arguments suggest that while artificial language studies of this nature form an important part of the evidence base, they must be interpreted as complementary to studies of existing languages and writing systems.

Overall, our results provide a strong demonstration of the impact of the orthographic density of a writing system on the precision of orthographic representations. Using an artificial language approach, we varied orthographic density across two artificial writing systems, while controlling all other stimulus and participant factors that confound this comparison in studies using natural languages. Our results challenge existing cognitive and neurobiological models of position coding in reading, and support the argument put forward by Frost (2012b) that orthographic representations are shaped by the statistical structure of the writing system one learns to read (see also Lerner et al., 2014). We look forward to using this method to delineate how the complex associations between orthographic, phonological and semantic information across the world's writing systems shape the acquisition of the reading skill.

CHAPTER SIX: MORPHOLOGICAL PROCESSING WITHIN THE VENTRAL STREAM

Do readers integrate morphological information during print-to-meaning mapping along the ventral stream?

Lally, C., Auer, T., Fischer-Baum, S., & Rastle, K. (in revision). Do readers integrate morphological information during print-to-meaning mapping along the ventral stream?

6.1 Abstract

The ventral stream is a hierarchical network in which readers decode orthography to access the meanings of words during reading. We used representational similarity analysis to investigate whether morphological information mediates the ventral stream print-to-meaning transformation. Hypothetical representational dissimilarity matrices expressed precise cognitive predictions about word similarities based on orthographic, semantic and morphological properties. Participants silently read these words while we recorded neural responses using fMRI. Our results indicate a graded hierarchy of abstraction from print to meaning within the ventral stream. Neural representations sensitive to orthography were located in posterior regions while representations sensitive to semantics were located in anterior regions. Readers formed intermittent orthographic representations for letter strings associated with morphemes; however, these representations were formed regardless of whether the stimulus could be parsed fully into morphemes. We discuss theoretical implications and consider how future applications of representational similarity analysis could advance our understanding of the neural basis for morphological processing.

All experiment materials, behavioural data, and analyses are available on the Open Science Framework: https://osf.io/yczpu/?view_only=59e65836bb6e49c5871a885d4d855efa.

6.2 Introduction

The ability to read is a learned skill rather than an inborn human capacity. Yet, skilled readers are able to read over 200 words per minute (Brysbaert, 2019b), accessing the meanings of different configurations of arbitrary visual symbols with ease. Therefore, a major question within cognitive neuroscience is how the brain transforms representations of visual symbols to meaningful linguistic information. Recent research suggests that this transformation involves multiple neural levels of representation, including orthographic representations of letters, and semantic representations of word meanings (Fischer-Baum et al., 2017, Taylor et al., 2019). These processes have been localised to the ventral stream, a neural pathway that reflects statistics of natural language (Dehaene et al., 2005; McCandliss et al., 2003; Vinckier et al., 2007; Woolnough et al., 2020). The current work uses representational similarity analysis (Kriegeskorte et al., 2008) to investigate the proposal that morphological knowledge mediates the ventral stream transformation of print to meaning (Rastle, 2019b).

6.2.1 Transformation of print to meaning within the ventral stream

The ventral stream, located in the left ventral occipito-temporal cortex, has been identified as a hierarchical network in which readers decode orthography to access word representations during reading (Dehaene et al., 2005; McCandliss et al., 2003; Vinckier et al., 2007; Woolnough et al., 2020). Dehaene et al. (2005) propose a feedforward account in which readers encode increasingly large units of orthographic information (such as letters, bigrams and small words) that become progressively more complex. Neural evidence suggests that these transformations occur along a posterior-to-anterior gradient within the ventral stream, and that the stored representations display sensitivity to linguistic probabilities within the writing system, such as frequency and word-likeness (Vinckier et al., 2007). Dehaene et al. (2005) propose that neural word representations are processed in a feed-forward manner, although more recently, Woolnough et al. (2020) observed orthographic processing in posterior regions before and after more anterior regions showed sensitivity to lexicality. This led the authors to suggest that ventral stream processing may incorporate feed-forward and feedback activity. Importantly, there is consensus that orthographic processing is influenced by the statistics of natural language, and that readers encode sub-lexical units of increasing complexity to access meaningful information about printed words.

In the past fifteen years, our understanding of these processes has been advanced by multivariate approaches, such as representational similarity analysis (RSA). RSA is based on the premise that stimuli that share similar representations will elicit similar neural response patterns in the relevant region (Kriegeskorte et al., 2008). By assessing the nature of information encoded within different brain regions, researchers have characterised various levels of neural representations that arise during reading within the ventral stream. Fischer-Baum et al. (2017) and Taylor et al. (2019) provided evidence for a posterior-to-anterior gradient in the ventral stream, in which orthographically similar words (*bark-dark*) showed similar patterns of neural activity in posterior regions, while semantically similar words (*bark-howl*) showed similar patterns of neural activity in anterior regions. Both studies demonstrate that these representations become gradually more abstract from the visual input and become increasingly linguistic in nature. For example, word representations become selectively more tuned to orthographic similarity independent of visual shape (Fischer-Baum et al., 2017) and letter representations are encoded with increasing invariance to position (Taylor et al., 2019). Combined, neural evidence suggests that ventral stream processing regions are hierarchically organised to reflect statistically salient information in the writing system.

6.2.2 The role of morphology in the ventral stream

The relationship between printed words and their meanings is often arbitrary in English. Printed words that look similar (*bark-dark*) do not have similar meanings, and printed words that mean similar things are spelled differently (*bark-howl*). However, morphological relationships in the writing system provide a degree of systematicity, as stems occur consistently in words with similar meanings (*unlock*, *relock*, *unlockable*), and affixes consistently modify the meanings of words (*unlock, undress, unclog*). Skilled readers capitalise on these "islands of regularity" (Rastle et al., 2000), accessing the meanings of printed words rapidly by decomposing letter strings into their morphemic constituents (*un*+*lock*; see Rastle, 2019b for a review).

Evidence from masked priming demonstrates that morphologically complex words facilitate faster recognition of their stem (*teacher-TEACH*) compared with non-morphological words with equivalent orthographic overlap (*window-WIND*) (Rastle et al., 2004). Notably, this benefit extends to words that appear to be morphologically related but have no semantic connection (*corner-CORN*) (Beyersmann et al., 2012; Beyersman et al., 2016; Meunier & Longtin, 2007; Marslen-Wilson et al., 2008; Morris et al., 2007; Rastle & Davis, 2008; Rastle et al., 2004). However, this priming advantage is eliminated when prime durations are extended (Rastle et al., 2000). This pattern has led to the proposal that an initial *morpho-orthographic* decomposition based on the appearance of morphological structure gives way to *morpho-semantic* decomposition in which semantic information constrains the initial segmentations (Rastle & Davis, 2008). Support for this characterisation comes from electroencephalography (EEG) and magnetoencephalography (MEG) studies demonstrating that changes in neural activity occur in two distinct time windows corresponding to morpho-orthographic and morpho-semantic processing (Lavric et al., 2007; Lavric et al., 2012; Lavric et al., 2011; Lewis et al., 2011; Morris et al., 2008; Morris et al., 2011; Solomyak & Marantz, 2010; Whiting et al., 2014).

If morphemes reflect salient statistical information along the mapping between print and meaning, then neural representations of morphemes should be integrated along the ventral stream hierarchy (Rastle, 2019b). Previous work supports this view, as multiple ventral stream regions are implicated in morphological processing (Bozic et al., 2007; Cavalli et al., 2016; Devlin et al., 2004; Gold & Rastle, 2007; Lewis et al., 2011; Pylkkänen & Marantz, 2003; Solomyak & Marantz, 2010; Zweig & Pylkkänen, 2003). Whilst orthographic processing is localised posteriorly and semantic processing is localised anteriorly, intermediate regions demonstrate sensitivity to morphology that is distinct from these processes (Gold & Rastle, 2007). Further anterior, the middle and superior temporal gyri display increased levels of activation for words with a morphological appearance (*corner*) relative to genuine morphologically complex words (*teacher*, Whiting et al., 2014). This finding is interpreted as semantic constraint, with more effortful processing attributed to semantic inconsistency. Further, diffusion tensor imaging has shown that morphological processing skill is associated with properties of ventral stream white matter tracts (Yablonski et al., 2019) that support information transfer across different cortical regions. Therefore, evidence suggests that morphological knowledge is involved in integrating multiple levels of representation along the ventral pathway.

This discussion exposes a limitation in neural proposals of reading, which are ambivalent to the regularity that morphology provides to the print-to-meaning mapping. Theories advanced by Dehaene et al. (2005) and Woolnough et al. (2020) are both limited to substring frequency, as morphemes are not distinguished from other frequent orthographic combinations. As a result, existing proposals are unable to explain neural evidence for morphological processing independent of orthographic processing. Neither account considers how the hierarchical organization of the ventral stream may be influenced by sub-lexical constituents which are not only frequent, but also play a functional linguistic role.

6.2.3 Research aims

In the current work, we used RSA to characterise the multiple levels of representations that arise in the ventral stream during skilled reading. Specifically, we sought to investigate whether morphological representations are integrated within this pathway. Our first aim was to localise neural sensitivity to orthography and semantic properties. Words with orthographic similarity were predicted to show similar patterns of activation in the most posterior regions, whereas words with semantic similarity were predicted to show similar patterns of activation in the most anterior regions. Our second aim was to probe for neural representations that were specifically morphological in nature, and investigate where they are situated relative to orthographic and semantic processes. Such representations can inform us of the functional contribution of morphology and establish whether readers form morphological representations that are distinct from sensitivities to orthographic or semantic properties. If so, we expected morphological representations to arise in intermediate regions between orthographic and semantic processing within the ventral stream. Words with morpho-orthographic similarities were predicted to display similar patterns of neural activity anterior to regions responsible for orthographic processing, as this would reflect early decomposition into recognised substrings. We predicted that words with morpho-semantic similarities would display similar patterns of neural activation in regions further anterior to those predicted to display morpho-orthographic sensitivity, as we predicted that representations would become constrained by semantics. Stimuli, data, and analysis scripts are openly available on the Open Science Framework.

6.3 Methods

6.3.1 Participants

Twenty-nine monolingual English speakers participated in this study. Participants were 18-30 years of age, right-handed, and had no history of learning disabilities or hearing or vision impairments. This study was approved under the Royal Holloway University Research Ethics Committee procedure and all participants provided informed consent prior to taking part. Participants were paid £20 in exchange for their time.

6.3.2 Stimuli

Ten sets of five words each were selected as targets. Each set shared an embedded letter string that featured the same letter sequence as a morpheme. For half of the sets this shared letter string was associated with a stem (e.g. act, tract, exact, enact, action); for the other sets it was associated with an affix (e.g. regret, reward, refuse, reclaim, refund). Words were controlled for frequency using the CELEX database (Baayen et al., 1995). Words within each set varied in orthographic, morpho-orthographic and/or morpho-semantic similarity to each other. These levels of similarity were cumulative, in the sense that words with morpho-orthographic similarity also had orthographic similarity as they shared an embedded letter string, and words with morpho-semantic similarity also had morpho-orthographic and orthographic similarity. Similarities are illustrated in Figure 1.

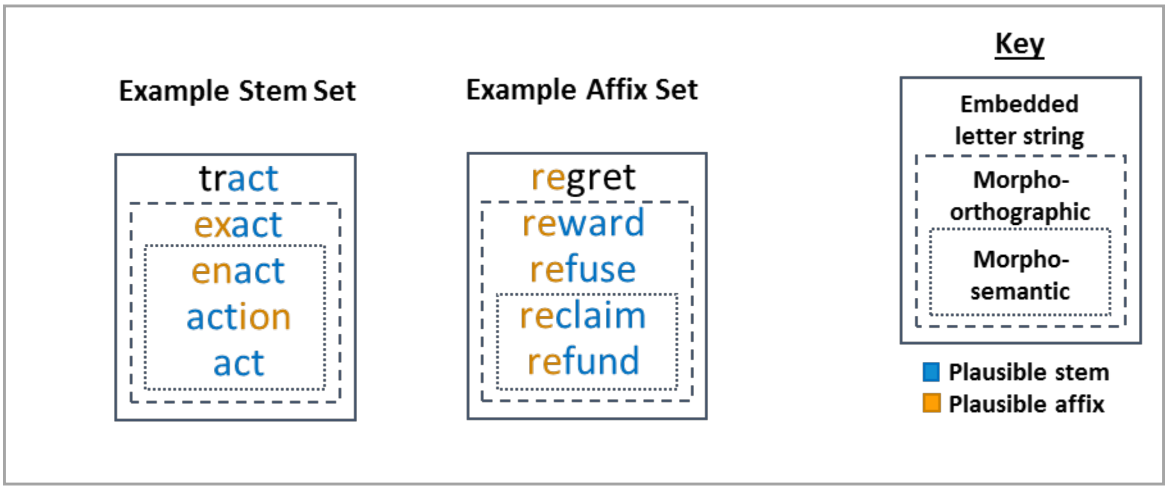

Figure 1. Demonstration of embedded letter string, morpho-orthographic and morpho-semantic relationships between words within stimuli sets.

Words with a shared embedded letter string contained a letter combination associated with a stem or an affix but did not have a viable morphological structure. An example of this is *tract*, which contains the letter sequence for a plausible stem (*act*) but does not contain a plausible affix. Therefore, the relationship of *tract* with other words within the set is purely orthographic, as the word cannot be parsed into constituent morphemes. Words with morpho-orthographic similarity had an apparent morphological structure (i.e. they contained a plausible stem and a plausible affix). These words could be parsed into constituent morphemes based on orthographic information; however, they did not have a semantic relationship with other words that appeared to contain the same morpheme. For example, *exact* can be decomposed into morphemes defined orthographically (*ex-*, *act*), but its meaning is not transparently related to the stem *act*, and it is unrelated in meaning to the genuine morphological words in the set (*enact, action, act*). Words with morpho-semantic similarity had a genuine morphological relationship with each other. These words shared a morpheme and had a morphological structure whereby some aspects of meaning were shared. Following the example stimuli sets, *enact* and *action* share a morpheme (*act*) that has a consistent meaning and each has a plausible affix that systematically modifies the meaning of the stem. We used latent semantic analysis ratings (LSA; Landauer & Dumais, 1997) ranging from zero (no semantic relation) to one (the same meaning) to confirm that on average, words with morpho-semantic similarity had higher semantic relatedness (0.40) than words that only had a shared embedded letter string (.04) or morpho-orthographic similarity (.09).

6.3.3 Representational dissimilarity matrices

We constructed five *a priori* representational dissimilarity matrices (RDMs) based on hypothesised progressive stages of visual word recognition (Figure 2). We hypothesised that each of these matrices would display the best fit at different regions within the ventral stream, based on the expectation that representations become increasingly abstract as readers extract meaning from print. Firstly, we predicted that words with shared orthography would demonstrate similar patterns of neural activation in posterior regions, and that words with shared meaning would demonstrate greater neural similarity in the anterior ventral stream. Secondly, we expected RDMs expressing morphological properties to best characterise neural patterns within intermediate ventral stream regions, as would be predicted if readers utilise morphological structure to derive meaning from print (Rastle, 2019b).

The first two RDMs predicted word dissimilarity independently of morphology. The first RDM predicted *orthographic* dissimilarity independently of morphological structure (e.g. l<u>at</u>e and <u>a</u>c<u>t</u>). Orthographic dissimilarity was calculated using Levenshtein distance measures (van der Loo, 2014), a continuous position-specific metric which counts how many letter additions, deletions and substitutions are required to change one word to another. Higher

Levenshtein scores indicated greater orthographic dissimilarity (e.g. late-act; LDM score: 3 vs. late-form; LDM score: 5). The second RDM expressed *semantic* dissimilarity, based on overlap in word meaning. Semantic dissimilarity was calculated using continuous inverse LSA similarity ratings, which are calculated from how often words co-occur in corpus context (Landauer & Dumais, 1997). Higher ratings indicated greater dissimilarity (e.g. plank-platform; LSA score: 0.44 vs. plank-read; LSA score: 0.97)

The third, fourth, and fifth RDMs were included to probe representations based on internal morphological structure. The purpose of these RDMs was to identify where representations based on morphological decomposition occur relative to representations of semantic and orthographic information. The third RDM predicted dissimilarity based on *embedded letter string* dissimilarity. In this RDM, words were classified as similar as long as they shared a letter combination associated with a stem (act, tract, exact, enact, action) or an affix (regret, reward, refuse, reclaim, refund), regardless of whether words had a plausible morphological structure that could be decomposed into constituent morphemes. The fourth RDM predicted *morpho-orthographic* dissimilarity, defined by words sharing an embedded letter string within a plausible morphological structure. Words classified as similar could be parsed as constituent morphemes but did not necessarily have a semantic relationship. Words with morpho-orthographic (*act-exact*) and morpho-semantic (*act-action*) overlap were coded as similar, whereas words with a shared embedded letter string without viable morphological structure (*act-tract*) were coded as dissimilar. The fifth RDM predicted *morpho-semantic* dissimilarity, based on a genuine morphological relationship. Words were coded as similar if they had a shared morpheme, a viable morphological structure and a semantic relationship. For example, *enact* and *action* were coded as similar to each other, but both were coded as dissimilar to *exact.* This is because *enact* and *action* are semantically related to the stem *act*, whereas *exact* is not. Predicted comparisons within embedded letter string, morpho-orthographic and morpho-semantic RDMs were binary coded as 0 (similar) or 1 (dissimilar) based on the criteria of each RDM.

All five RDMs were symmetrical, therefore only the lower triangular (diagonal half) of each matrix was included within analyses. This ensured that stimuli comparisons were not duplicated within each RDM and prevented stimuli from being compared with themselves. Each RDM was entered into a linear regression, and the variance of inflation factor (VIF) between each RDM was calculated to quantify the degree of multicollinearity between matrices. The VIF for each comparison was below 5, indicating a low degree of collinearity (Miles, 2014).

One goal of the current work was to investigate where morphological representations occur relative to orthographic and semantic processing in general. To accomplish this goal, we first needed a measure of whether a region processes orthographic or semantic information about written words independently of the morphological relationship between the words. This was achieved using the first two RDMs, which considered the orthographic and semantic dissimilarity of all word pairs that are not in the same morphological set. Analyses with these RDMs provided a morphology-independent measure of orthographic and semantic processing in different regions. The results with these RDMs were then compared to the next three RDMs. Morpho-orthographic and morpho-semantic RDMs focused specifically on morphological relationships, and did so using only comparisons between items in the same morphological set. As a result, non-morphological RDMs (orthographic and semantic dissimilarity) and morphological RDMs (morpho-orthographic and morpho-semantic dissimilarity) made use of non-overlapping subsets of the data. Therefore, RDMs characterising dissimilarity independently of morphology used different brain-based similarity comparisons to RDMs modelling similarity based on morphological properties. Determining whether morphological RDMs are correlated with the same regions as non-morphological RDMs can tell us whether morpho-orthographic processing and morpho-semantic processing are simply engaging more general orthographic and semantic representations, without concerns that the overlap is driven by common items in the analysis. The embedded letter string RDM made use of the entire data set. This comparison is theoretically relevant to both morphological and non-morphological processing. Comparisons between the embedded letter string RDM and the orthographic RDM allow us to determine whether specific regions encode word substrings (as suggested by Dehaene et al., 2005) as well as individual letters. This would be apparent if the embedded letter string RDM and the orthographic RDM were both significantly correlated with neural activity within a particular region. Since the embedded letter string RDM does not explicitly care about whether there is a morphological relationship between the string and the whole word, differences between this RDM and morpho-orthographic and morpho-semantic RDMs can reveal whether or not a region is specifically sensitive to morphology. For example, neural activity within an ROI was significantly correlated with the morpho-orthographic RDM but not the embedded letter string RDM, the results would indicate sensitivity to morphological structure.

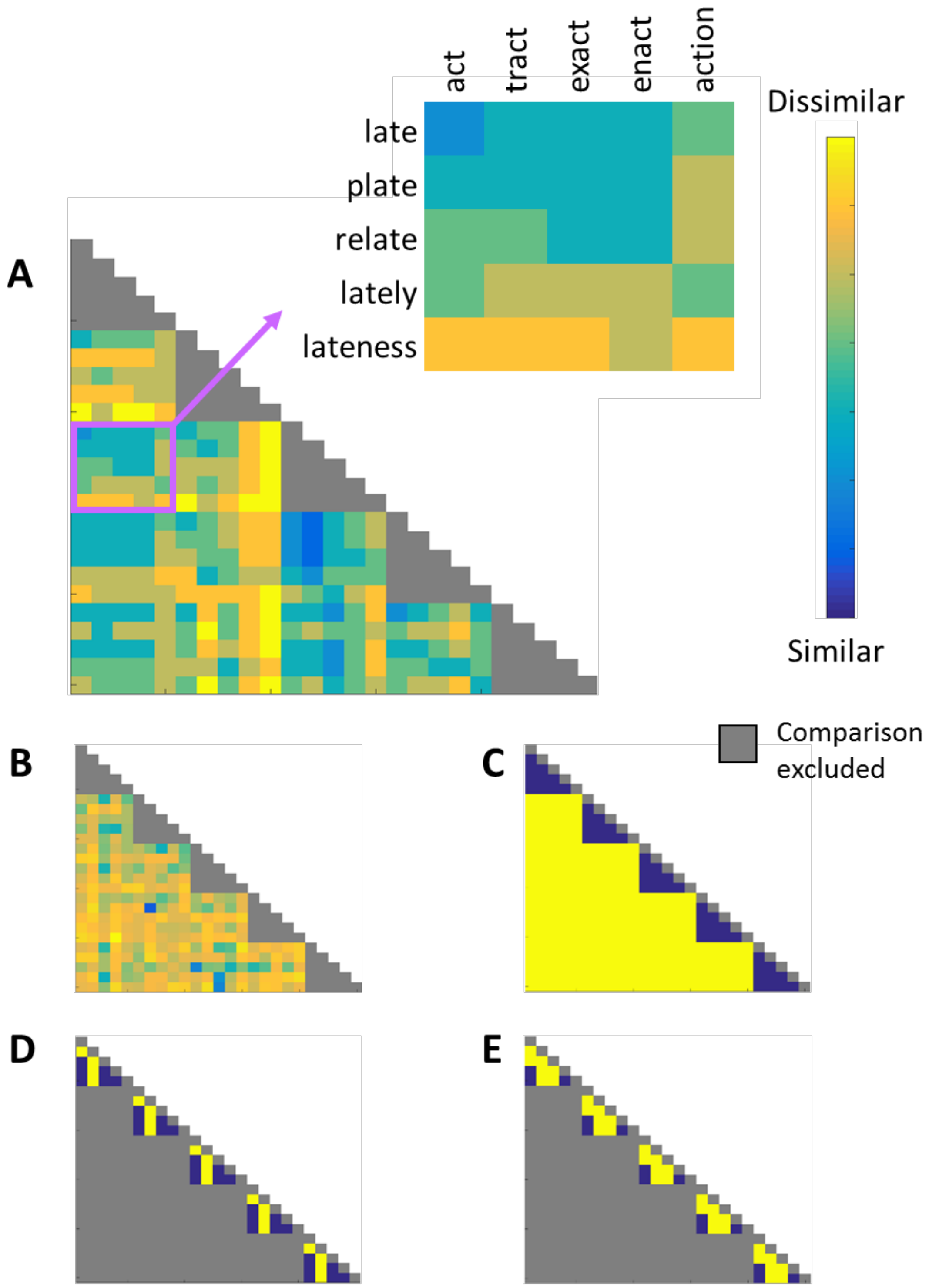

Figure 2. Lower diagonals of the predicted representational dissimilarity matrices (RDMs) based on (A) orthography, (B) semantics, (C) embedded letter strings, (D) morpho-orthographic structure, and (E) morpho-semantic structure. Higher values (in yellow) denote greater dissimilarity.

6.3.4 Scanner task

Participants completed a recognition task in the MRI scanner, in which they were presented with blocks of 30 words displayed in isolation. Participants were instructed to attend to the words and read each word silently; they were explicitly asked not to use rehearsal strategies. Each block was followed by a test item, and the task was to indicate whether a test item had appeared within the previous block by providing a button-press response. Test item accuracy was recorded as a measure of attention. Each block consisted of 40 randomised trials, which included 25 word stimuli, ten fixation-cross null events (25% of all trials, as recommended by Kriegeskorte et al., 2008), and five filler words which changed across each block in order to give the appearance of variation and increase the task difficulty. Filler items had a morphologically complex appearance and were matched to critical stimuli on frequency. Each item was displayed for 750 ms, followed by a fixation cross displayed for an inter-stimulus interval of 2750 ms (resulting in a stimulus-onset-asynchrony of 3500 ms). At the end of each block, participants were presented with a 1000 ms fixation cross, followed by a test word for 4000 ms. They were instructed to indicate whether the test word had appeared in the previous sequence or not. The test word was either a word that had appeared in the previous sequence, or a foil that had not appeared within the task at all. There were twenty-four blocks over four functional runs, which resulted in twelve repetitions of each of the stimuli. The duration of each run was 15 minutes and 24 seconds.

6.3.5 fMRI acquisition procedure

Functional MRI data were acquired on a 3T Siemens Trio scanner (Siemens Medical Systems, Erlangen, Germany) with a 32-channel head coil. Blood oxygenation level-dependent functional MRI images were acquired with a multi-band echo-planar imaging (EPI) sequence with a repetition time (TR) of 2000 ms, 2.5 mm isotropic voxels and an inter-slice gap of .625 mm (25%), flip angle of 78 degrees, echo time (TE) 30 ms and 48 slices with a 78 x 78 data matrix. The acquisition was transverse oblique, angled to avoid the eyes and to achieve whole-brain coverage. The scanning session featured four functional runs, in which 458 volumes were acquired for each run. Five dummy scans were added at the start of each functional run and excluded from statistical analyses. To assist with anatomical normalization we acquired a T1-weighted structural volume using a magnetization prepared rapid acquisition gradient echo protocol (TR = 2250 ms, TE = 2.98 ms, flip angle of 9 degrees, resolution of 1 mm isotropic, 256 x 256 x 192 matrix). We acquired field maps after the first two functional runs, in order to address signal dropout and correct for spatial distortion. Field maps were acquired using the same geometry as the EPI sequence in the functional runs.

6.3.6 Regions of interest

Four 10 mm^3 spherical ROIs were selected within the left hemisphere (Figure 3). Selection of these ROIs was *a priori* and theoretically driven, based on prior work on reading in the ventral stream (Gold & Rastle, 2007; Taylor et al., 2019; Vinckier et al., 2007). From posterior to anterior, ROIs were located in the inferior occipital cortex, posterior fusiform gyrus, anterior fusiform gyrus and the middle temporal gyrus. The three most posterior ROIs were based on the findings of Vinckier et al. (2007), who localised orthographic areas within the ventral stream that corresponded with hierarchical orthographic processing during word reading. The two most posterior ROIs were based on exact MNI co-ordinates of ROIs used by Vinckier et al. (2007). The co-ordinates for the third ROI were averaged across co-ordinates of the three most anterior ROIs identified by Vinckier et al. Our ROIs (10 mm^3 sphere) were larger than those used by Vinckier et al. (4 mm radius); therefore, averaging was necessary to avoid overlap. In line with Fischer-Baum et al. (2017), we decided to increase the size of our ROIs as our pre-processing did not include spatial smoothing. By enlarging the ROIs, we aimed to account for individual variability within the ventral stream (Glezer & Riesenhuber, 2013). The fourth and most anterior ROI was located in the middle temporal gyrus, based on peak co-ordinates for lexical-semantic activation identified by Gold and Rastle (2007), which were converted from Talaraich to MNI space. ROIs were created using MarsBaR (Brett et al., 2002) and anatomically labelled using the Automated Anatomic Labelling Atlas (AAL, Tzourio-Mazoyer et al., 2002). Prior to analyses, ROIs were warped into each participants' native space and overlaid with a grey matter mask using the Automatic Analysis de-normalisation module (Cusack et al., 2015).

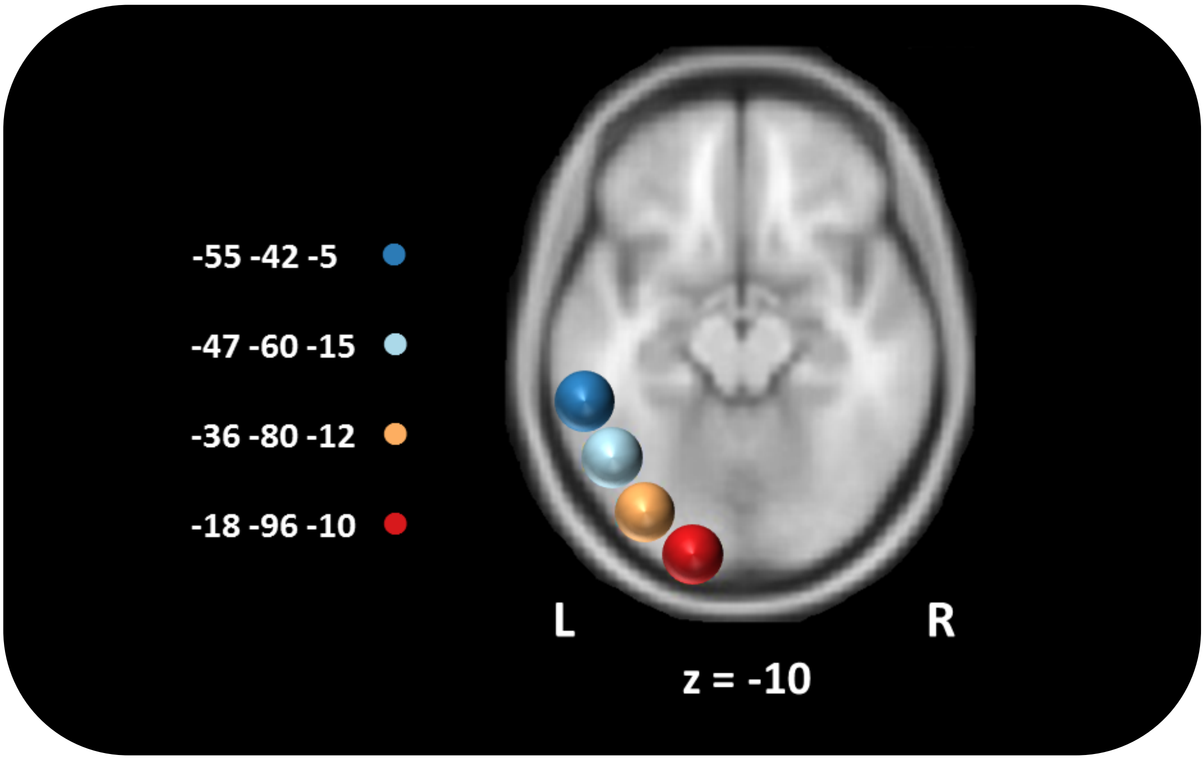

Figure 3. Locations of 10 mm^3 spherical regions of interest in MNI space.

6.3.7 fMRI analyses

Data pre-processing and the subsequent univariate analyses were conducted using the Automatic Analysis pipeline framework (Cusack et al., 2015) based on SPM12 (Friston et al., 1994). Pre-processing included motion correction, slice time correction and co-registration of the fMRI images to the T1 image, as well as segmentation of the T1 image into tissue types. Grey matter masks were created for each participant based on tissue probability being higher for grey matter than for any other tissue types. Five participants were excluded from analyses due to head movement exceeding 4 mm.

Whole-brain univariate analyses were conducted to observe whether participants elicited typical activation associated with reading during the experiment. Spatial smoothing was applied using a 5 mm full width by half-maximum Gaussian kernel prior to the univariate analyses. The first-level contrast estimate images were normalised into Montreal Neurological Institute (MNI) space using a diffeomorphic anatomic registration through an exponentiated lie algebra algorithm (DARTEL, Ashburner, 2007). For each participant we used a model including the six motion correction parameters as covariates and a first-level contrast comparing activation during reading all word stimuli to null-event trials in which participants viewed a fixation cross (Words>Baseline). At group-level, we conducted a one-sample t-test to determine whether the mean group-level activation statistically differed from zero at each voxel in the brain.

The representational similarity analyses largely followed the same procedure as that used in other visual word recognition studies (Fischer-Baum et al., 2017; Taylor et al., 2019). The procedure is depicted in Figure 4. No spatial smoothing or normalisation was applied during pre-processing for the RSA analyses, since differences in adjacent voxels may provide valuable information for pattern analyses (Kriegeskorte et al., 2008). We constructed a general linear model which included separate regressors for each of the word stimuli versus baseline, and the corresponding contrast estimate maps were entered in the ROI-based RSA analyses as implemented in the CoSMo MVPA toolbox (Oosterhof et al., 2016). As a result, we obtained a measure of the neural response to each word stimuli within each ROI for each participant. We then constructed observed neural dissimilarity matrices, which demonstrated how similar neural patterns of activation were between each word stimuli within each ROI for each participant. These were computed based upon one minus the Spearman rank correlation between the neural response for each word and every other word within the stimuli sets. The observed neural dissimilarity matrices were then compared to each of the hypothesized RDMs for stem and affix sets using a Fisher-transformed Pearson correlation coefficient. Correlation co-efficients were averaged across stem and affix sets for each RDM in each ROI. For each participant, this resulted in a correlation value for each RDM within each ROI, which expressed how well the RDM characterised the observed neural dissimilarity between words. Correlations were then analysed at group-level by conducting a one-sample t-test to determine whether correlations significantly differed from zero. As ROIs were selected prior to analyses, and RSA hypothesis were devised *a priori*, ROI group-level results were not corrected for multiple comparisons. The same procedure was observed in similar published RSA literature investigating the neural basis of reading, including Fischer-Baum et al. (2017) and Taylor et al. (2019).

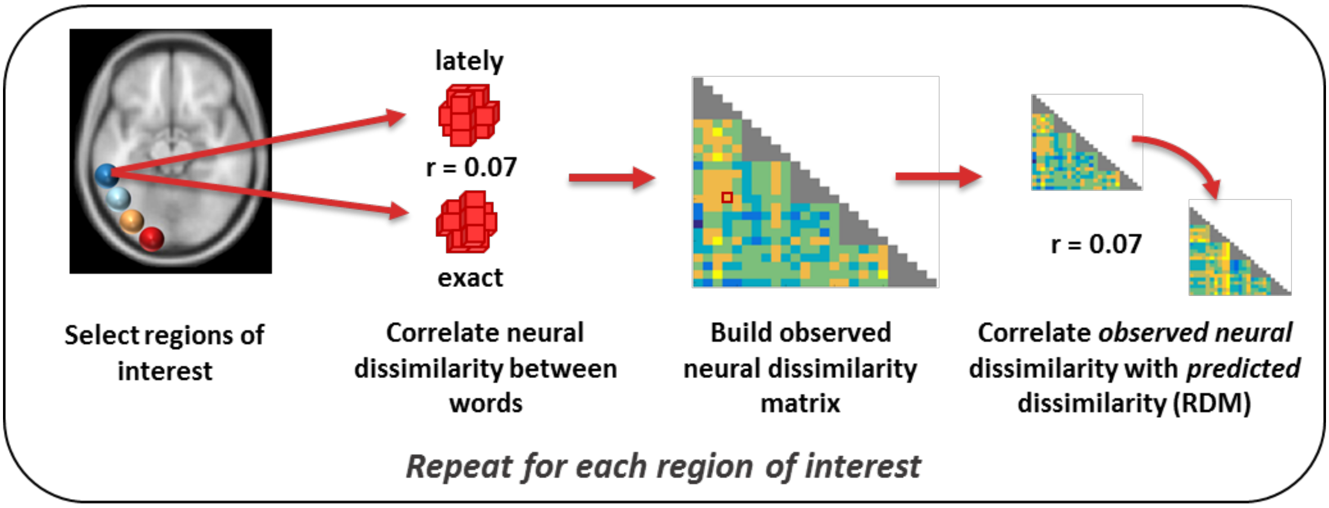

Figure 4. Illustration of the MVPA–RSA region of interest analyses. BOLD response was measured while participants read each word.

6.4 Results

6.4.1 Behavioural performance

Mean accuracy for the recognition task was 83% (*SE*: 2%). Performance was statistically assessed using signal detection theory (Macmillan, 2002), where $d' = 0$ would indicate no differences between signal and noise (chance performance). A one-sample t-test indicated that participants d' prime scores significantly differed from chance ($d' = 2.32$, $t(23) = 12.26$, $p < .001$). This result indicates that participants attended to the task and read the words presented on screen.

6.4.2 Univariate results

Figure 5 displays group-level activation during word reading, which was computed through the contrast Words>Baseline. Table 1 lists clusters of activation after applying an uncorrected threshold set at $p < .001$ at voxel-level and a threshold set at $p < .05$ corrected by family-wise error (FWE) rate at cluster-level. The threshold for corresponding FWE-corrected peaks within clusters was set to $p < .01$. In the left hemisphere, the Words>Baseline contrast was associated with significantly increased activation in the fusiform gyrus, the inferior and middle occipito-temporal cortex and the precentral gyrus. In the right hemisphere, activation was significantly higher in the lingual gyrus, fusiform gyrus and the inferior and middle occipito-temporal cortex. These neural regions overlapped with those that are typically engaged during reading. For example, left ventral occipito-temporal cortex contains locations identified in the local combination detector model (Dehaene et al., 2005). Therefore, the univariate results further confirmed that participants engaged in reading behaviour during the task and that the expected neural representations were engaged during reading processes.

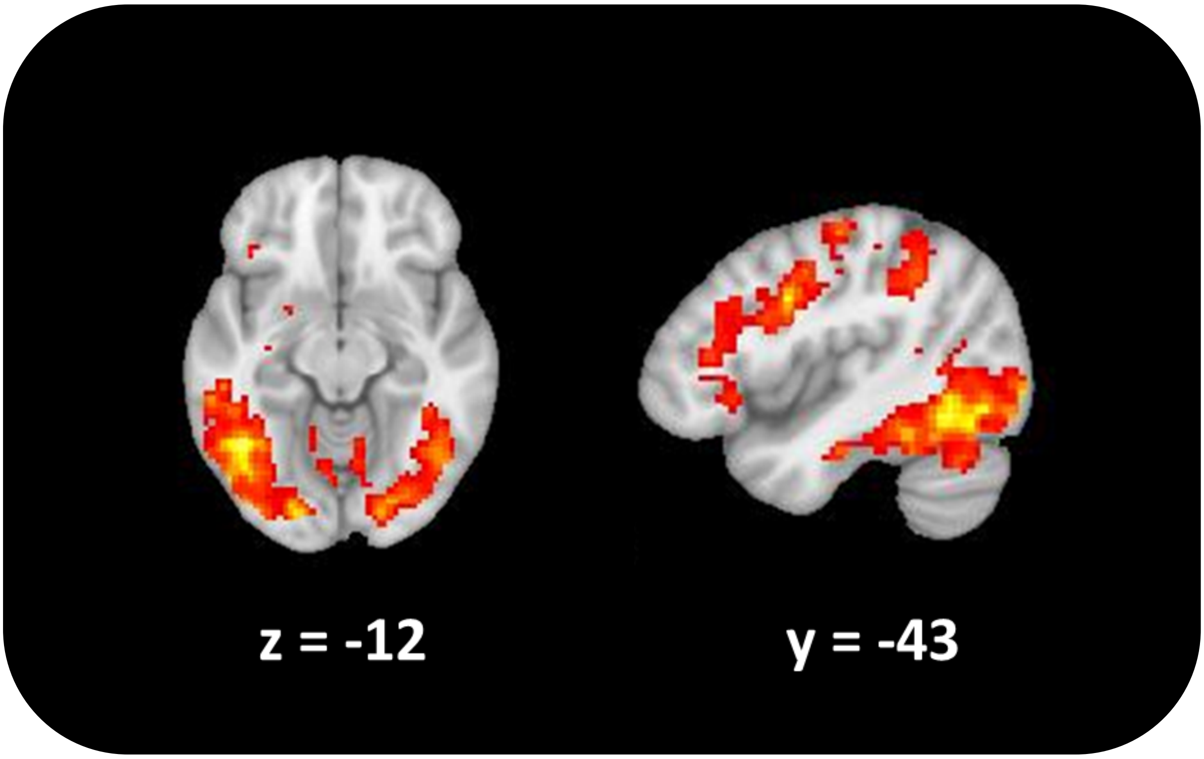

Figure 5. Univariate activation during word reading vs. viewing a fixation cross, uncorrected p = .001 cluster-forming and p = .05 FWE-corrected cluster extent thresholds.

Table 1.

Whole brain univariate group-level results for Words>Baseline contrast.

Brain Region	L/R	Peak Voxel			k	*Z*	Cluster *p-value*	Peak *p-value*
Fusiform Gyrus	L	-35	-50	-18	3206	10.38	< .001	< .001
Middle Occipital Cortex	L	-18	-92	2		9.7		< .001
Middle Occipital Cortex	L	-40	-85	-2		8.98		< .001
Lingual Gyrus	L	-15	-90	-10		8.8		< .001
Fusiform Gyrus	L	-45	-62	-15		8.58		.001
Fusiform Gyrus	L	-45	-40	-18		8.35		.001
Inferior Occipital Cortex	L	-30	-82	-8		8.19		.001
Fusiform Gyrus	L	-40	-70	-12		7.92		.002
Middle Temporal Gyrus	L	-48	-48	5		7.58		.005
Lingual Gyrus	R	20	-88	-5	2928	1.07	< .001	< .001
Fusiform Gyrus	R	38	-42	-22		8.94		< .001
Middle Occipital Cortex	R	28	-90	5		8.7		< .001
Calcarine	R	20	-95	2		8.48		.001
Middle Temporal Gyrus	R	50	-65	5		7.76		.003
Cerebellum	R	38	-65	-22		7.35		.009
Precentral Gyrus	L	-60	0	25	2349	7.58	< .001	.005
Precentral Gyrus	L	-42	2	30		7.37		.008

Results show brain regions with activation clusters after applying an uncorrected p = .001 cluster-forming threshold, which clusters survive a cluster-extent threshold set at FWE-corrected *p* = .05 and a peak-level threshold set at FWE-corrected *p* = .01. L/R = laterality (left/right); peak voxel co-ordinates are reported in Montreal Neurological Institute (MNI) standard space; k = cluster size; Z = z-value for peak voxel.

6.4.3 Representational similarity analysis

Figure 6 displays mean correlations between the predicted RDMs and the neural dissimilarity observed within each ROI. As expected, the orthographic RDM (based on Levenshtein distance measures) was significantly correlated with patterns of neural activation observed in the two posterior ROIs in the left hemisphere: the inferior occipital cortex, $t(23) = 5.42$, $p < .001$, and posterior fusiform gyrus $t(23) = 3.11$, $p < .01$ (Figure 6A). The semantic dissimilarity RDM was significantly correlated with neural patterns observed in the most anterior left ROI, the middle temporal gyrus, $t(23) = 2.21$, $p < .05$ (Figure 6B). The embedded letter string dissimilarity RDM was also significantly correlated with patterns of neural activation observed in the two posterior ROIs within the left hemisphere, the inferior occipito-temporal cortex, $t(23) = 4.56$, $p < .001$, and the posterior fusiform gyrus, $t(23) = 3.47$, $p < .01$ (Figure 6C). Morpho-orthographic and morpho-semantic dissimilarity RDMs (Figures 6D and 6E) were not significantly correlated with the neural patterns of activation observed in any of the ROIs (*p-values* > .05; Figures 6D-E).

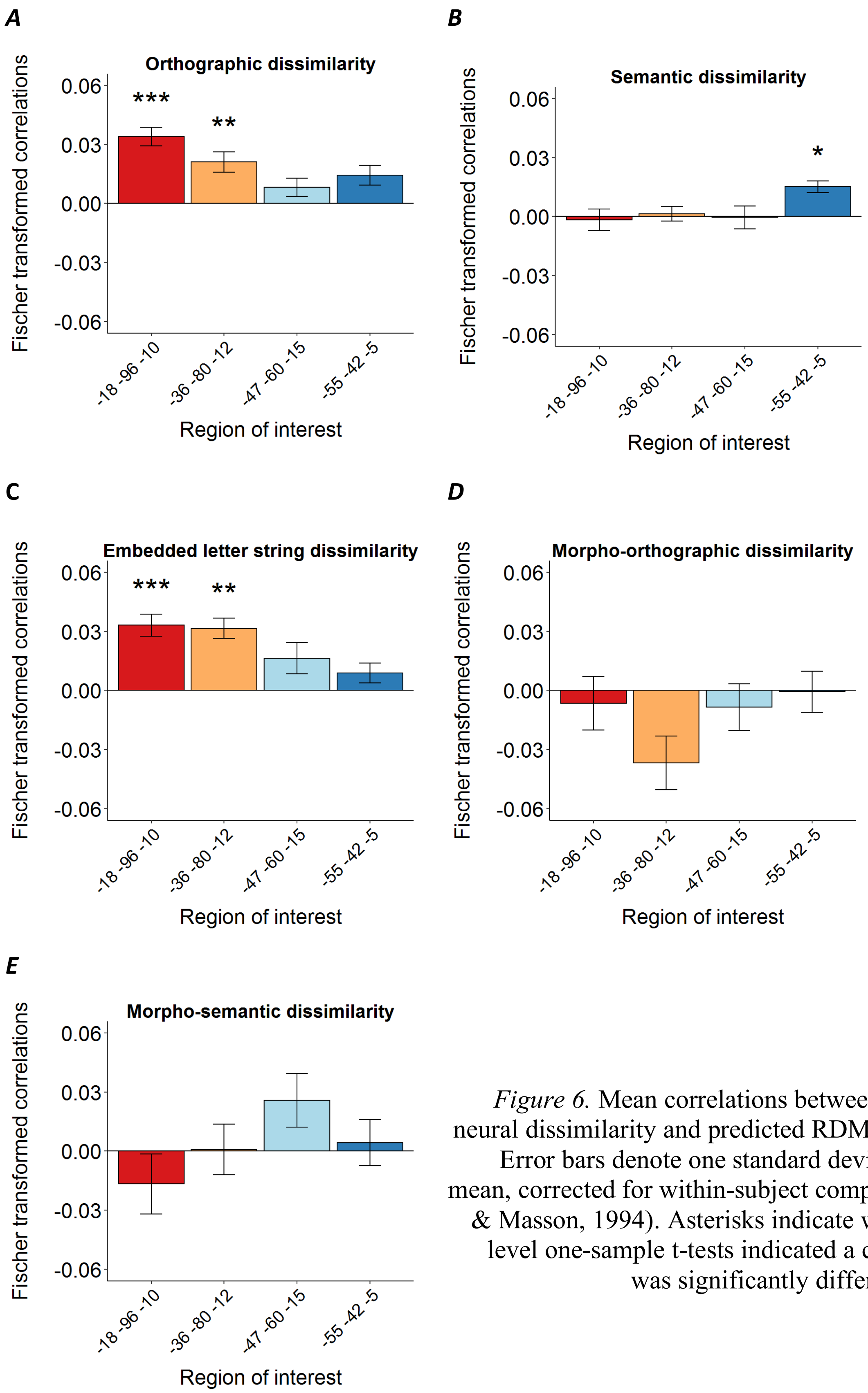

Figure 6. Mean correlations between the observed neural dissimilarity and predicted RDMs in each ROI. Error bars denote one standard deviation from the mean, corrected for within-subject comparison (Loftus & Masson, 1994). Asterisks indicate whether group-level one-sample t-tests indicated a correlation that was significantly different from zero.

6.5 Discussion

Readers form print-to-meaning mappings via multiple hierarchical levels of neural representations (Fischer-Baum et al., 2017; Taylor et al., 2019). These representations demonstrate sensitivities to the statistics of the writing system, such as legal letter combinations or word frequency. Morphological representations are an important intermediate link between orthography and meaning and therefore should be integrated within these processes (Rastle, 2019b). In the current work, we used RSA to characterise the multiple levels of representation that arise during reading. First, we localised neural representations sensitive to orthographic and semantic information. Following previous work (Fischer-Baum et al., 2017; Taylor et al., 2019), we predicted that words with similar orthography would elicit similar patterns of activation within posterior ventral stream regions and words with similar meanings eliciting similar patterns of activation in anterior regions. Then we investigated whether morphological representations mediate these levels of representation.

6.5.1 Transformation of print to meaning within the ventral stream

Our first research aim was to localise neural representations that were sensitive to orthography and semantics. RSA analyses identified neural representations that were sensitive to orthographic information in posterior ventral stream regions and semantic information in anterior regions, as predicted by our first hypothesis. Neural patterns correlated with representations based on orthographic dissimilarity within the two most posterior ROIs, located in the left inferior occipital cortex and left posterior fusiform gyrus. These two ROIs were correlated with RDMs predicting orthographic dissimilarity from individual letter overlap (Figure 2A & Figure 6A. *act-late*) and embedded letter string dissimilarity (Figure 2C & Figure

6C, *act-tract*). Sensitivity to orthographic structure has been observed in ROIs with similar co-ordinates in previous work (Taylor et al., 2019; Vinckier et al., 2007). These results align with previous findings, which demonstrate that the fusiform gyrus is sensitive to orthographic properties such as co-occurring letter probabilities (Binder et al., 2006, McCandliss et al., 2003, Vinckier et al., 2007). In addition, these findings support the proposal that the ventral stream becomes more attuned to larger fragments of words in a posterior-to-anterior gradient, extending from individual letters to frequent substrings (Dehaene et al., 2005). Representations based on semantic dissimilarity were correlated with the most anterior ROI, located within the middle temporal gyrus (Figure 2B & Figure 6B). This region has been associated with semantic processing in previous work (Fischer-Baum et al., 2017; Gold & Rastle, 2007; Taylor et al., 2019, in which neural activity is similar for words with shared meaning regardless of orthographic similarity.

Our initial findings support the over-arching hypothesis that print-to-meaning mapping occurs via multiple levels of neural representation, which are transformed in a posterior-to-anterior gradient along the ventral stream. Orthographic RDMs were correlated with neural activity in posterior regions, and the semantic RDM was correlated with activity in anterior regions. Our findings also provide evidence that readers encode progressively large orthographic units, as posterior regions were correlated with dissimilarity based on shared individual letters and embedded letter strings. This supports the prediction that readers encode increasingly large fragments of text within the ventral stream (Dehaene et al., 2005; Vinckier et al., 2007, Woolnough et al., 2020).

6.5.2 The role of morphology in the ventral stream

Our second aim was to investigate whether reading gives rise to neural representations that are specifically morphological in nature, and where these representations are situated relative to orthographic and semantic representations within the ventral stream. Rastle (2019) proposed that neural representations of morphemes should be integrated within the ventral stream, as they reflect statistical regularities that promote direct print-to-meaning mapping. However, existing neural proposals models of reading (Dehaene et al., 2005; Woolnough et al., 2020) do not consider morphology beyond substring frequency. By using RSA to compare words with morpho-orthographic and morpho-semantic similarities, we were able to investigate the representational contribution of morphology beyond providing frequent combinations of letters.

If morphological structure gives rise to neural representations mediating the mapping between orthography and semantics, representations should be observed in intermediate ventral stream regions. Contrary to our hypotheses, we did not detect neural activity that was sensitive to morphological structure. There was no evidence for representations based upon morphological structure, as none of the ROIs were significantly correlated with the morpho-orthographic or morpho-semantic RDMs. In the absence of any significant correlation, there are two possibilities: Either reading does not give rise to representations that are specifically morphological in nature, or our design did not detect them. We consider methodological limitations and theoretical reasons as to why this may be the case.

Lack of evidence for morphological representations could be attributed to low power. One of the key aspects of our design was to investigate the neural basis for morphological representations independently of orthographic and semantic representations. To achieve this, it was essential to ensure that orthographic and semantic RDMs used different brain-based similarity calculations compared to morphological RDMs. The number of comparisons within morphological RDMs (100 comparisons per matrix) were substantially reduced relative to the other matrices (500 comparisons per matrix for orthographic and semantic RDMs and 600 comparisons per matrix for embedded letter string RDM). The number of comparisons was also lower than in similar previous studies (Baeck et al., 2015: 180 comparisons; Fischer-Baum et al., 2017: 595 comparisons; Rothlein & Rapp, 2014: 264 comparisons; Taylor et al., 2019: 276 comparisons). This reduction in power may have affected our ability to detect small correlations, and future work should ensure a greater number of comparisons to rule out this possibility.

A further consideration is that readers may not have engaged in morphological processing due to the nature of the task. Wang et al (2018) demonstrated that semantic processing in the visual word form area is dependent on task demands, as correlations of RDMs modelling different semantic theories varied based on whether the task required taxonomic (feature-based) or thematic (situation-based) semantic judgements. We selected a recall task as it involved passive viewing of words to reflect naturalistic reading. The task enabled us to include a measure to ensure that participants were attending to stimuli, whilst minimising extraneous neural activity generated from providing a response. As we were investigating the role of morphology in extracting meaning from print, a task that required semantic judgement may have been more appropriate. Recording neural behaviour while readers engage with morphologically complex words in a range of tasks may provide a clearer picture.

Alternatively, it is possible that morphological representations did arise, but our analyses did not detect them. We opted to use a region-of-interest approach as we had specific predictions about the integration of morphological representations within the ventral stream. However, this approach depends on the assumption that the regions selected process this type of information and we cannot rule out that neural representations sensitive to morphological properties may be situated elsewhere. To investigate this possibility, we conducted exploratory analyses using a whole-brain RSA searchlight approach (in which neural patterns are extracted from each voxel within the brain and a pre-specified neighbourhood radius of surrounding voxels). We applied the same pre-processing steps outlined for the previous RSA analyses. We created a grey matter mask (based on voxels exceeding 10% probability of containing grey matter) for each participant by de-normalising and co-registering EPI images to grey matter tissue segmentation. Searchlight analyses were conducted in each participants' native space by using a 100-voxel spherical searchlight on each voxel within the grey matter mask. This produced whole-brain statistical maps demonstrating correlations between each RDM and patterns neural activity for each participant. These maps were normalized to MNI space and submitted to a one-sample *t*-test to identify voxels in which correlations were significantly larger than zero at group-level. These analyses did not reveal any significant correlations between morpho-orthographic and morpho-semantic RDMs, based on uncorrected p = .001 cluster-forming and p = .05 FWE-corrected cluster extent thresholds.

We also considered the possibility that morphological representations may occur within the ventral stream (or elsewhere in the brain), but our RDMs may not accurately characterise them. One of the key features of RSA is that construction of RDMs requires precise predictions about the properties of theories being tested (Fischer-Baum et al., 2017). Morphological RDMs were modelled upon discrete stages of morpho-orthographic and morpho-semantic processing, based upon the theory that readers decompose words into possible constituent morphemes prior to lexical access (Rastle et al., 2004). Comparisons within these RDMs were categorically coded as either similar or dissimilar, depending on whether they had a shared form-based appearance of morphology (morpho-orthographic) and whether words shared a meaningful morphological relationship (morpho-semantic). As Fischer-Baum et al. (2017) outline, the successful application of RSA relies upon the assumption that theories underlying RDMs are characteristic of the information represented at neuronal level. Hence, it is important to consider alternative cognitive theories that may explain why morphological effects arise.

Connectionist theories propose that readers encode morphology as statistical regularities that reflect convergence of orthographic and semantic codes (Joanisse & Seidenberg, 1999; McClelland & Patterson, 2002; Plaut & Gonnerman, 2000). According to this view, morphological relationships arise from systematic convergence between word forms and their meanings. Consequently, connectionist theories would characterise morphological relationships on a graded continuous scale rather than through categorical distinctions (such as morpho-orthographic and morpho-semantic). Other proposals have suggested that morphological processing could arise from statistical regularities in orthography alone. Lelonkiewicz et al. (2020) have suggested that morphemes have a statistical orthographic advantage over other frequent letter combinations, as they are position-specific (i.e. they consistently appear at the beginning or the end of a word). They propose that position-specificity frequency can explain why divergent priming effects occur between words with plausible and implausible morphological structure (*corner-CORN* vs. *window-WIND*; Rastle et al., 2004) and thus argue that morphological processing can be explained on a purely orthographic basis. Future work could use RSA to construct multiple RDMs according to alternative morphological theories and compare how well each RDM correlates with neural activity within the ventral stream. This would enable researchers to delineate between competing accounts of morphological processing and determine the cognitive theory that most accurately characterises the neural representations that arise from morphology.

To summarise, we did not find evidence for neural representations that were morphological in nature. However, we cannot conclude that these representations do not occur during skilled reading. Model-based calculations for our theoretical RDMs may not have been a good proxy for the neural activity that arises during morphological processing, or representations may not have been detected due to limitations in power. We have outlined how future work can use RSA to test competing accounts in order to provide clarification on unresolved questions around the role of morphology within the ventral stream.

6.6 Conclusion

Our findings consolidate previous work and support the proposition that readers extract meaning from print via hierarchical representations in a posterior-to-anterior direction along the ventral stream. There was evidence that readers form representations for embedded letter strings that contain letter combinations associated with morphemes; however, these representations seem to be formed on an orthographic basis. Neural patterns that arose from words that could not be decomposed into constituent morphemes (e.g. *regret, tract*) elicited similar patterns of activation for words with a viable morphological structure (e.g. *re-claim, en-act*). Therefore, we did not find any evidence for any representations that were specifically morphological in nature. This work demonstrates an innovative approach to investigating the neural basis of multiple representational levels proposed to arise during morphological decomposition. We have proposed how RSA can be applied in future research to address limitations within the current study, and to delineate between alternative cognitive accounts of morphological processing. Understanding the neural representations that underpin these processes can greater inform how structural properties within the writing system contribute to the mapping between print and meaning during skilled reading, and how this expertise is integrated into wider processes.

CHAPTER SEVEN: DISCUSSION

The processes that contribute to visual word recognition are highly versatile. Successful recognition is achieved via a complex set of interacting cognitive processes, which are shaped by the written environment. In order to establish a fully integrated account of reading, we must first recognise the factors that drive readers' adaptability. The overarching aim of this work was to advance understanding of the nature and deployment of representations arising during the early stages of word reading. The studies presented within this thesis investigated how representations are shaped by both short-term and long-term factors. Chapters 3 and 4 explored how the saliency of different orthographic cues is influenced by immediate context, whereas Chapters 5 and 6 examined whether orthographic representations are moulded by long-term knowledge of the writing system. This final chapter evaluates the evidence presented within this thesis, considers theoretical implications for existing models of reading, and proposes some future directions for research.

7.1 How are representations shaped in the short-term by immediate context?

Identifying a written word requires readers to integrate multiple sources of visual and linguistic information simultaneously. There is wide indication that these cues are adaptably weighted based on situational factors, including characteristics of the word, relationships with other known words, and the context in which the word appears. Consequently, there are dynamic differences in how orthographic information is integrated online across individual instances of visual word recognition. Past research has investigated how readers integrate cues from various different levels of orthographic structures, including feature-level cues (e.g.

Kinoshita & Kaplan, 2008; Marcet & Perea, 2017), word-level cues (e.g. Grainger & Jacobs, 1994; Reicher, 1969; Wheeler, 1970) and sentence-level information (e.g. Federmeier et al., 2007; Snell & Grainger, 2019; Staub, 2015). However, there has been little cross-investigation into how cues at different levels in the processing hierarchy interact with each other.

The first half of this thesis investigated how letter identification is influenced by surrounding orthographic context. Letter identification sits at an interesting mid-point in visual word recognition, as individual letters are combinations of low-level visual features, and are also assembled alongside other letters to form component parts of a word. From a simple perspective, letter identification could thus be considered as both a start and an end point of recognising different orthographic constituents. However, previous research indicates that these processes are not distinct from each other. Instead, there is evidence that orthographic information cascades across hierarchical levels during visual word recognition. The word superiority effect serves as a prime example that letter identification is not solely guided by properties of the individual letter, but also by orthographic information from surrounding letters within the string (Reicher, 1969; Wheeler, 1970). In Chapters 3 and 4, we used the word superiority effect as a mechanism to test the scope of influence from surrounding orthographic information, and the extent to which this information leaks into the processing of various different orthographic structures. This enabled us to develop an account of how readers integrate low-level visual information and high-level sentence information during word recognition, in situations where cues provided either collaborative or conflicting information.

Chapter 3 explored whether effects of word level knowledge on letter identification are influenced by surrounding sentence context. There was substantial variability in letter identification facilitation due to a corresponding word representation, which was dependent upon whether the word aligned with predictions from sentence context. The word superiority effect was larger in high constraint sentences where the word was the most predictable candidate, compared with low constraint contexts in which many words had an equal likelihood of occurring. Critically, word representations did not provide any facilitative advantage for letter identification if the word violated sentence predictability expectations. These findings suggest that readers neglect precise letter level processing if the higher-level knowledge provides a strong enough indication of what the upcoming word will be. In other words, the precision of orthographic processing depends on the perceived accuracy with which words can be anticipated from sentence context.

Chapter 4 investigated whether word level cues modulate readers' dependence on fine-grained feature level information. Visually similar letters are typically more confusable than dissimilar letters (Marcet & Perea, 2017), which suggests that letter identities are encoded with initial uncertainty. We proposed that higher-level word cues may enrich letter identification processes and subsequently reduce readers' reliance on low-level visual distinctions. Orthographic context (whether letters appeared in a word, pseudoword or consonant string) and visual similarity (whether readers discriminated between visually similar or dissimilar letters) had independent effects on letter identification. In the absence of an interaction, we were unable to establish whether orthographic context mediated the effect of visual similarity specifically. However, the magnitude of the effects did indicate that higher-level orthographic information plays a greater role than lower-level visual feature information in letter identification. We proposed that visual similarity effects were encapsulated within word-level effects because readers could use orthographic knowledge to refine potential letter candidates while visual feature information is accumulated.

Across both chapters, the findings consistently indicated that orthographic cues are hierarchically integrated, with descending weights allocated to sentence-, word- and letter-level information. Readers had greater difficulty discriminating between visually similar letters (e.g. *e/c*) compared with dissimilar letters (*e-k*), although visual feature similarity effects were eclipsed by differences in word-level information. Overall letter identification was more accurate if the letter appeared in a legal orthotactic combination, and further still if the letter appeared in a known word (e.g. *well/wcll*). Thus, in single word recognition, lexical knowledge proved to be the driving force in letter identification. Within a sentence, letter identification was further facilitated by information from preceding context if it provided additional corroboration for the surrounding letter string (e.g. *the child fetched water from the well*). However, conflicting sentence-level information produced an inhibitory effect, whereby the lexical advantage was eliminated if the word violated readers' expectations (e.g. *the old man was writing his well*). This suggested that readers rely preferentially on sentence-level contextual information when it is available.

Overall, the evidence presented in the first half of this thesis indicates that letter identification processes are signal-contingent; readers adapt orthographic processing based on the information available in order to balance precision with efficiency. Cues from higher-level knowledge can cause lower-level cues to become redundant, or they can even have inhibitory consequences for word or letter recognition if they contradict information from the bottom-up signal. The biased weighting towards higher-level knowledge could reflect the refinement of orthographic candidates (such as words, sub-lexical units or letters) whilst lower level information is still being accumulated, which can in turn inform the optimal depth of orthographic processing required. This provides support for cascaded processing; whereby earlier stages of processing do not have to be complete before later stages begin (McClelland, 1979). Critically, these processes are not encapsulated within individual words, as the influence of surrounding orthographic context on letter identification extends beyond word boundaries to other words within a sentence. The theoretical implications of these findings are considered later in this chapter.

7.2 How are representations shaped in the long-term by knowledge of the writing system?

The second half of this thesis focused on how the weighting attributed to various orthographic cues emerges from long-term experience with the writing system. The representations that support visual word recognition are likely to arise in response to the text environment (Frost, 2012b). Therefore, a full understanding of visual word recognition requires 'deep appreciation' of the salient characteristics that emerge within a given written language (Rastle, 2019a). If reading reflects the writing system, it is important to consider the nature of the input (*what is read*) as well as the processes used to analyse this information (*how it is read*). Based on this premise, Chapters 5 and 6 investigated how representations are shaped by statistical regularities within a writing system, and how these are encoded within the brain.

Chapter 5 investigated whether flexibility in letter position coding is dependent on orthographic density. Our artificial language learning paradigm demonstrated that readers encode letter position with greater precision in dense orthographies with many anagrams relative to sparse languages with very few anagrams. This was shown through greater detection of untrained stimuli formed by transposing letters of trained stimuli. The findings provide evidence that flexibility in letter position coding is not universal across languages, hence it cannot solely be attributed to general cognitive or neurobiological factors. Instead, the results indicate that letter position coding is determined through exposure to the written environment.

Readers use distributional information to determine the precision of orthographic processing required for efficient and accurate word recognition.

In Chapter 6, we used representational similarity analysis to characterise the neural representations that arise during reading of morphologically complex words. We proposed that readers might form specialised neural representations based on orthographic and semantic properties of morphemes, due to the regularity they provide to the mapping between print to meaning (Rastle, 2019b). The results indicated that readers form print-to-meaning mappings via multiple hierarchical levels of neural representations along the ventral stream. Neural patterns of activity in posterior regions showed sensitivity to orthographic information, whereas anterior regions demonstrated sensitivity to semantics. Readers formed intermittent orthographic representations for letter strings associated with morphemes; however, these representations were formed regardless of whether the stimulus could be parsed fully into existing morphemic constituents. Therefore, we were unable to confirm that these representations were morphological in nature. Due to limitations in power, follow-up work is required to fully understand whether readers form neural representations for morphemes, and whether such representations reflect distributional knowledge or discrete stages of morphological processing. Our results could also indicate that orthographic representations associated with intermediate sub-lexical structures reflect sensitivities to other distributional statistics in the writing system, such as bigram frequency.

Chapters 5 and 6 illustrate that readers form long-term weightings for different sources of orthographic information based on statistical salience within the writing system. By integrating distributional information, readers can determine the precision of orthographic processing required to differentiate between words and develop intermediate representations to assist mappings between print, sound and meaning. Chapter 5 in particular provides powerful evidence of how readers of two different writing systems develop comparable proficiency at visual word recognition, whilst demonstrating striking differences in their underlying representations. Ultimately, these findings show that the nature of the text environment has a direct impact on how words are learned, and formation of the corresponding representations that support visual word recognition.

Multiple theories suggest that cross-linguistic differences in visual word recognition are due to differences between writing systems. The most distinguished proposals were initially developed to explain differences in demands based on consistency between orthography and phonology. Examples include the orthographic depth hypothesis (Katz & Frost, 1992; Schmalz et al., 2016) and psycholinguistic grain size theory (Ziegler & Goswami, 2005). Both theories suggest that readers analyse different size orthographic units in order to achieve maximal consistency within the writing system. Under this premise, readers of consistent orthographies will more readily decode words via grapheme-phoneme correspondences. In contrast, low consistency orthographies prompt greater reliance on whole-word lexical processing, or encoding of larger orthographic units such as syllables, rimes and morphemes. These proposals therefore include specific predictions that readers form representations for sub-lexical structures that provide systematic mappings between meaning, sound and print. Further, their principles can be extended to explain differences in letter position coding. Readers of dense orthographies with many anagrams may rely on a larger grain size to analyse larger combinations of letters in order to tell words apart.

As our findings suggest that word recognition processes are optimised through gaining expertise within a writing system, further insights can be gained from theories of reading acquisition. Several accounts of reading development highlight the written environment as a central factor in forming optimal word representations. Amalgamation theory (Ehri & Wilce, 1983), the lexical quality hypothesis (Perfetti, 2007) and the lexical tuning hypothesis (Castles et al., 2007) predict that reading acquisition is characterised by continuous refinement of word representations through the accumulation of print experience. Almagamation theory suggests that refinement occurs through repeated encounters, as readers build 'access routes' to efficient word recognition by repeatedly encoding visual symbols with systematic linguistic information (e.g. phonemes or morphemes, Ehri & Wilce, 1983). The lexical tuning hypothesis predicts that word representations are also shaped through exposure to written information that can be differentiated in some way, as this enables word recognition processes to continually adapt to meet the requirements of a growing written vocabulary (Castles et al., 2007). For example, learning new words may increase neighbourhood size and subsequent competition, hence readers must tighten their precision in how these words are identified in order to maintain accurate recognition.

Theories of cross-linguistic processing and reading acquisition provide converging arguments for how readers make optimal use of information within the written environment, and the fundamental role that learning plays. Hence, they have the scope to explain why readers are sensitive to distributional saliences, and why cross-linguistic differences arise. The next section outlines how our findings can be accounted for by existing models of visual word recognition, and the challenges for interpreting our results if sub-lexical processes are constrained to the needs of a specific orthography. Going forward, theories of cross-linguistic acquisition could be fundamental in bridging this gap if they can be reconciled with existing models of skilled reading in which the role of the written environment is underspecified.

7.3 Implications for theoretical models of reading

The evidence presented within this thesis establishes three broad findings in relation to visual word recognition. Firstly, readers hierarchically integrate orthographic information with a weighted bias towards higher-level knowledge. Secondly, the influence of surrounding orthographic information on sub-lexical processing extends beyond individual word boundaries to other words within sentence context. Finally, the weightings assigned to various sources of orthographic information are shaped by salient characteristics of the writing system. Each of these findings has theoretical implications for cognitive and computational models of reading. In this section, I outline the extent to which contemporary models of reading can account for these principles.

7.3.1 Descending hierarchical weightings biased toward top-down knowledge

The findings presented within this thesis consistently show that readers routinely attribute greater weighting to higher-level orthographic knowledge compared to information from smaller orthographic units. This suggests that cues are hierarchically integrated, with broader contextual cues determining the precision with which readers analyse lower-level sub-lexical details. We propose that readers sacrifice precision in lower-level processing if higher-level cues provide sufficient evidence of a word's identity, in order to maintain an optimal balance between efficiency and accuracy during visual word recognition.

These hierarchical weightings are well characterised by cascaded processing, where later stages of word processing are implemented before earlier stages are completed (McClelland, 1979). Cascaded processing is a prominent feature in the interactive activation model (McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982) and the successors that implement it, including the dual-route cascaded model (Coltheart et al., 2001) and the connectionist dual-process models (CDP+; Perry et al., 2007; CDP++; Perry et al., 2010; Perry et al., 2013). In these models, nodes representing different size orthographic units are dynamically weighted and send excitatory and inhibitory feedback to each other and other layers within the network. Interactive activation models are able to explain why the influence of larger orthographic units (such as orthographic word status) eclipses the impact of cues from smaller orthographic units (such as visual feature similarity). Feature nodes send activation to letter nodes, which are simultaneously receiving activation feedback from corresponding word nodes in which they are featured. Consequently, feedback from word-nodes play a greater role in activating a letter representation compared to bottom-up activation from feature-level information alone. Therefore, cascaded processing can account for why effects of visual feature similarity are outweighed by cues from lexical information when available.

Alternatively, readers may generate multiple codes during visual recognition, based on orthographic units of various sizes. The greater weighting attributed to higher-level information may be a consequence of the representation of a larger orthographic unit being activated in a shorter timeframe than that required to activate all of its individual component parts. This principle is adopted by the multiple read-out model (MROM; Grainger & Jacobs, 1996), which proposes that readers recognise words or word properties via multiple codes with adjustable criteria. For example, readers may accept or reject a letter string in a lexical decision task based on activation levels for a specific word surpassing a threshold (the M criterion), or if summed activation levels for all active word representations surpass a threshold (the Σ criterion). Alternatively, a letter string may be rejected as a word if activation does not reach a certain level within a timeframe (the T criterion). The MROM explains the word superiority effect as activation surpassing the threshold for a larger orthographic unit (the word) prior to its component parts (individual letters). This argument can explain why top-down word level information had a relatively larger impact than bottom-up feature information in establishing letter identities in Chapter 4, if lexical or orthotactic thresholds are met prior to individual letter thresholds from feature information.

One further possibility is that information from higher-level knowledge assists in strengthening reader predictions, which may reduce the depth of fine-grained orthographic analysis required. This explanation aligns with Bayesian models of reading, which propose that visual word recognition is achieved by readers combining tentative evidence with knowledge of prior probability (Norris, 2006; Norris et al., 2010; Norris & Kinoshita, 2012). From a Bayesian perspective, one could argue that bottom-up analysis of lower-level orthographic features constitutes the tentative evidence and integration of top-down orthographic knowledge shapes the priors of the expected visual word representation. Unlike the majority of reading models, Bayesian models do not assume that visual word recognition is underpinned by specialised orthographic processing, or any processes that are distinct from those used to recognise other visual objects (Norris & Kinoshita, 2012). The greater influences of higher-level orthographic cues (i.e. word status) relative to lower-level visual cues (i.e. feature information) may not reflect specialised lexical processing, instead they may be due to readers having stronger priors for letter combinations associated with known word representations, which requires less detailed analysis of the visual evidence.

A wide range of models are able to account for the weighting assigned to higher-level linguistic cues relative to lower-level orthographic cues, either through cascaded processing, generation of multiple codes or through Bayesian predictions of probability. Thus far, I have outlined how these different principles can account for descending hierarchical weightings when words are read in isolation. However, our work also demonstrates that readers integrate orthographic information beyond single word boundaries, drawn from surrounding words within sentence context. In the next section, I consider how existing models of word reading can account for the influence of sentence-level information on sub-lexical processing.

7.3.2 Sentence-level influences on within-word processing

Past research has indicated that correspondence with an existing word representation provides a golden ticket to more accurate and efficient letter identification (Reicher, 1969; Wheeler, 1970). However, this work has predominantly focused on words presented in isolation. The work presented in Chapter 3 demonstrates striking evidence to the contrary when words appear within a sentence. Correspondence with an existing word representation can be beneficial if the word representation aligns with the target. However, existing word representations are also disruptive if the letter string shares orthographic similarities with another word that is more likely to appear within the given context. When a word violates sentence-level expectations, there is no evidence to suggest that letter identification is any more accurate in words compared to pseudowords. This indicates that readers rely on lexical cues only in the absence of constraining sentence information. When words appear in sentences, readers preferentially use cues from surrounding context to narrow the pool of potential word candidates. In this situation, letter identification is facilitated by correspondence with a selective set of context-appropriate words, rather than any known lexical representation.

Evidence of sentence-level influences on sub-lexical processing poses major theoretical implications for cognitive models of word reading, which have typically focused on how readers recognise words in isolation (Coltheart et al., 2001; Grainger & Jacobs, 1996; Harm & Seidenberg, 2004; McClelland & Rumelhart, 1981; Perry et al., 2007; Perry et al., 2010; Perry et al., 2013; Plaut et al., 1996; Rumelhart & McClelland, 1982; Seidenberg & McClelland, 1989). Most of the models that include sub-lexical letter-level processes do not consider how readers integrate information beyond single-word context, whereas models of sentence reading tend to eschew sub-lexical processing and include whole words as the smallest unit of representation (Engbert et al., 2002; Engbert et al., 2005; Reichle et al., 2003). As a result, there is a substantial disconnect between models of single word and sentence reading. Our findings suggest that models of sentence reading and single word reading cannot be additively combined, as this would be dependent on modelling words as isolated components that individually slot into a larger sentence structure. Due to the influence from surrounding words on sub-lexical processes, it is clear that this is not an accurate depiction of reading behaviour. Instead, this work highlights the need for an integrated model that considers basic orthographic processes within meaningful sentence contexts.

As identified in Chapter 3, the OB-1 Reader is the closest candidate with the potential to explain sentence context effects on sub-lexical processing, as it is able to outline how graded word recognition in sentences and sub-lexical processing can be integrated. The OB-1 Reader features a word recognition module where letter information across the visual field (including across other words) assists in activating lexical candidates (Snell et al., 2018). Individual words are recognised via a combination of bottom-up constituent bigram activity, competition with other word representations and top-down contextual predictability. Importantly, Snell and Grainger (2019) assert that word recognition should not be segregated into letter-level processing and conscious identification. Instead, they propose that readers consider tentative representations at various intermediate levels of processing based on information from multiple surrounding words within the sentence. The authors further suggest that this behaviour can be explained by the broader principles of cascaded processing, whereby a word does not have to be fully recognised in order to activate higher-order features. Therefore, contextual predictability effects on sub-lexical processing can be explained by word representations being partially activated at various levels based on top-down input from sentence context. This account aligns with our empirical findings in Chapter 3, as readers appeared to identify a word based on a "good enough" match to the expectation from sentence context, which resulted in lower precision for letter-level processing. Under this account, influences from other words on sub-lexical processing are an extension of cascaded processing using information from a higher multiple-word level within the representational word recognition hierarchy.

In theory, Bayesian models are also able to account for sentence-level effects with their existing principles, as they assume that word recognition processes are signal-contingent. According to Bayesian models, words are recognised by accumulating noisy visual evidence and comparing it with expectations from prior probability (Norris, 2006; Norris et al., 2010; Norris & Kinoshita, 2012). When identifying a word, readers may use surrounding sentence context to adjust the priors used to analyse provisional evidence whilst it is being accumulated. This argument can explain why a lexical advantage is narrowed to a predictability advantage in sentence context, as only a reduced set of word candidates would have stronger priors relative to other letter combinations. Further, stronger priors (driven by predictability from sentence context) reduces the precision with which the evidence is analysed. This can explain why inhibition effects arise in unpredictable neighbours of predictable targets.

7.3.3 The role of the writing system

The final significant finding within this thesis is that the weightings assigned to various sources of orthographic information are optimised according to salient characteristics of the writing system. Models of reading should be sensitive to the role of the written environment as a key factor in forming optimal word representations, and enable flexibility for processes to differ across languages. Previous work has demonstrated how the architecture of existing models can be modified to process language-specific properties, for example, alternative letter position coding schemes can replace slot-based coding to produce transposed letter effects (Davis, 2010; Gomez et al., 2008; Grainger & Whitney, 2004; Whitney, 2001). Similarly, model frameworks have been adapted to incorporate morphological processing (see Gonnerman et al., 2007; Taft, 1994; Taft, 2006; Taft & Nguyen-Hoan, 2010). However, a full theoretical account of visual word recognition must also be able to explain how universal cognitive processes interact with salient properties of different writing systems to explain how cross-linguistic differences emerge (Frost, 2012a; Frost, 2012b; Share, 2008).

Interactive activation models are limited in this respect, as prior knowledge of the writing system is assumed and processing is hardwired. Activation and inhibition connections are static and based on fixed prespecified metrics such as word frequency (Coltheart et al, 2001; Grainger & Jacobs, 1996; McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982). Consequently, these models have little to say about the role of the writing system as the input, and do not model learning, which restricts their ability to explain how reading processes and corresponding representations may vary across languages and/or through exposure to a particular writing system.

In contrast, connectionist models incorporate learning, which provides indication of how word recognition processes may change through reading experience. The triangle model is based on the premise that words are recognised via weighted connections between units representing orthographic, phonological and semantic properties (Harm & Seidenberg, 2004). Critically, connection weightings are adjusted based on repeated activation and error feedback to reflect salient distributional information within the writing system. This principle entails that the triangle model can account for readers using different mechanisms or strategies depending on the orthography (Seidenberg, 2011).

Connectionist dual-process models incorporate learning within the sub-lexical TLA network (Perry et al., 2007; Perry et al, 2010), which has been implemented in multiple languages including English (Perry et al., 2007; Perry et al, 2010), Italian (Perry et al., 2014a) and French (Perry et al., 2014b). However, learning relies heavily on exposure to large training sets in which word pronunciations with grapheme-phoneme correspondences are explicitly provided. Based on this input, the TLA sub-lexical network learns to extract letter combinations as graphemes and insert them into a template, which is predefined and manually modified to suit the characteristics of different orthographies. Arguably, learning within connectionist dual-process models is more indicative of generalisation from existing known rules rather than through the emergence of salient characteristics. Previous commentary has criticised these models for their reliance on supervised learning, suggesting that the initial explicit provision of thousands of correct pronunciations creates an unrealistic learning environment (Zorzi, 2010). Instead, learning environments could be simulated through unsupervised statistical learning, as implemented in models of acquisition (e.g. Dufau et al, 2010; Hutzler et al., 2004). These developments would not only improve CDP models' abilities to demonstrate how orthographic weightings emerge, they may also permit the flexibility to demonstrate how orthographic information is differentially weighted in different linguistic environments.

Our findings can be interpreted under Bayesian models of reading, which place notable emphasis on the role of the environment. If word recognition is achieved by assessing noisy evidence against knowledge of prior probability, then the priors that evidence is compared against will be shaped by previous exposure to the writing system. Notably, Bayesian models of reading explicitly account for cross-linguistic differences in visual word recognition, by clearly defining the roles of universal perceptual processing and environmental factors from the reading environment. Norris and Kinoshita (2012a) propose that 'orthographic processing is universal; it's what you do with it that's different'. They suggest that the same basic perceptual processes are applied to processing orthographic information in all languages. Cross-linguistic differences then arise based on how readers use this information depending on established mappings within the writing system of a given language. For example, Norris and Kinoshita (2012a) suggest that letter position is encoded with a degree of perceptual uncertainty across all orthographies, which increases in precision specifically during word identification. This is dependent on the precision required to achieve optimal word discrimination under the demands of the writing system. In recent years, there has been emerging support for this argument, as transposed-letter effects have been observed in low-level perceptual tasks (e.g. same-different tasks) in orthographies that do not typically show transposed-letter effects in lexically driven tasks (e.g. lexical decision), such as Hebrew (Kinoshita et al., 2012) and Korean (Lee et al., 2021).

Finally, the role of the written environment is also addressed in multiple neuro-biological models of reading, including local combination detector model (Dehaene et al., 2005) and Grainger and colleagues' (2016) visual model of reading. According to the local combination detector model, readers recognise words using a series of hierarchical detectors that increase in size and process increasingly complex orthographic information within the ventral stream. There is substantial evidence to suggest that the ventral stream is sensitive to the statistics of natural language (Vinckier et al., 2007; Woolnough et al., 2020). Larger detectors are proposed to encode frequently recurring substrings, such as morphemes or multi-letter graphemes, which enable readers to form neural representations based on salient sub-lexical units (Dehaene et al., 2005). We proposed that this explanation can be extended to explain differences in letter position coding across dense and sparse orthographies, as readers may need to consider positional information from a larger window of letters to reliably differentiate between words. Alternatively, the visual model of reading proposed by Grainger et al. (2016) proposes that skilled readers recognise words by analysing coarse- and fine-grained codes simultaneously (see also Grainger & Ziegler, 2011). Coarse-grained codes rapidly generate whole-word orthographic forms from bigrams, whereas fine-grained codes comprise precisely ordered orthographic chunks associated with graphemes and morphemes. Reliance across two codes with varying levels of precision provides flexibility to explain how readers adapt the precision of orthographic processing across languages, or even across tasks or contexts.

7.3.4 Summary

Existing models of visual word recognition vary in the extent to which they can account for our findings. Models must incorporate flexibility in the precision of orthographic processing as the optimal degree varies locally across different words and contexts, as well as cross-linguistically across different orthographies. The majority of models of single word reading can account for the greater influence of higher-level orthographic knowledge relative to lower-level orthographic details, either through cascaded processing, generation of multiple orthographic codes or Bayesian probabilities. However, the majority of these models are not able to explain how sub-lexical processing is modulated by orthographic information from surrounding words in sentence context. Conversely, models of sentence reading do consider influences on visual word recognition from surrounding context, but sub-lexical processing tends to be underspecified. This limitation reduces the classes of models that can account for our findings to those that consider both sentence-level and sub-lexical processing. The two most successful candidates are the OB-1 Reader model and Grainger et al.'s (2016) visual model of reading, although the principles of Bayesian models can also be interpreted to provide a compatible account.

When interpreting our findings, one of the main limitations for many existing models of reading is that they do not consider how processes are shaped by the written environment. Connectionist models incorporate the capacity for learning, but it is unclear how learning processes are forged from characteristics of the input. Bayesian models highlight the role of the environment in shaping readers' prior knowledge, however, there is not an explicit explanation on how this information is integrated long-term. Notably, neuro-biological models show considerable aptitude for explaining how processes are shaped by the written environment. Both the local combination detector model (Dehaene et al., 2005) and Grainger and colleagues' (2016) visual model propose that neuro-biological structures can flexibly encode orthographic units of different sizes based on optimal structures within the writing system. As outlined previously, limitations in existing models of skilled reading could potentially be addressed by incorporating principles from models of reading acquisition or theories underpinning cross-linguistic differences. However, further work is required to understand how these accounts would be integrated.

7.4 Limitations and future directions

This section considers some general limitations, and proposes how these can be addressed in future work. In addition, I consider a future agenda for how research can build upon the current work and further advance our understanding of representations that arise during visual word recognition.

7.4.1 Limitations

Each experimental chapter has highlighted individual limitations associated with each study. Notably, interpretation of some findings was restricted due to issues with power. This was the case in Chapter 4, in which one of the hypotheses was dependent on detecting an interaction between feature-level and word-level factors. Whilst we can use power simulations to obtain a more specific estimate of the required sample size, practical limitations may persist for obtaining a large enough sample to detect smaller effects or interactions. Future research could overcome this limitation and increase the practical feasibility of larger sample sizes by encouraging data collaboration across research institutions. Adopting this approach would enable us to collect rich large sample datasets that capture word recognition behaviour across a wide range of different orthographic conditions (see Adelman et al., 2014, for an example with masked priming). This resource could enable us to answer complex questions in which multiple aspects of the orthographic hierarchy are simultaneously considered.

A proportion of the neuroimaging analyses presented in Chapter 6 were also potentially underpowered. There is still little consensus on how to conduct power calculations for MRI analyses, particularly with more recent multivariate techniques (Cremers et al., 2017). We based our participant sample sizes on similar previous RSA studies (Fischer-Baum et al., 2017; Taylor et al., 2019), however we had not accounted for the reduction in item-based power when we removed specific comparisons. Future research designs should pre-empt the number of items required for well-powered comparisons and predictions, based on the expected effect size of correlations between hypothetical representational dissimilarity matrices and observed neural dissimilarity. It is currently unclear how these estimations would be formed; thus methodological clarity is required within the field.

7.4.2 Future directions

Each study shared the common aim to understand how specific word recognition processes are shaped by the written linguistic environment, whether this refers to immediate context or long-standing representations based on properties of the writing system. The findings have demonstrated that readers dynamically adjust the weight attributed to different sources of orthographic information depending on the cues available. In particular, precise scrutiny of low-level features is reduced if higher-level information provides sufficient cues for successful word recognition. More broadly, these findings illustrate how specific reading processes usually studied in isolation are influenced by other factors. This highlights the consequences of studying cognitive processes as component parts and reveals how the overall picture might change when we consider how these processes interact. The current work has tapped into just some of the aspects of the representational hierarchy when recognising printed words. There is ample opportunity to expand and investigate how other processes are influenced in light of the orthographic information available. An example could include investigating how predictability from sentence context impacts recognition of letter-transposition neighbours relative to letter-substitution neighbours (e.g. *the architect measured the angle/angel/ankle*). Based on most letter coding schemes, letter-transposition neighbours should be more confusable with the target than letter-substitution neighbours. However, this difference may be eliminated in sentence contexts where readers may adopt a shallower analysis of letter-level information based on predictability expectations. By systematically pitting different cues against each other, we can develop a more comprehensive account of how orthographic information is hierarchically integrated.

On a similar theme, the sentence reading work presented in Chapter 3 could be advanced by delineating between sentence-level effects of unpredictability and implausibility on sub-lexical processing.[8] Our understanding of how sentence expectations modulate sub-lexical processing could be more nuanced if we had differentiated contexts that were unlikely (*the football was kicked into the goat*) from contexts that referred to semantically incongruent, or impossible, situations (*the queen wore the sparkling gold crowd*). As we did not make this distinction, we are unable to conclude definitively whether lower letter identification accuracy in unpredictable words was due to the expectation of a more predictable candidate, or due to an implausible anomalous word that violates reading expectations entirely. We may expect differences in reading behaviour based on this distinction, as effects of predictability deviate from effects of plausibility elsewhere in the sentence reading literature. For example, implausible words prompt longer overall gaze durations and more regressions than unpredictable words (Rayner et al., 2004; Veldre & Andrews, 2018). Unpredictable words produce a delayed positive increase in N400 amplitude, whereas truly implausible words do not evoke an increased N400 response at all (Van Petten & Luka, 2012). Future work could draw the distinction on how unpredictability and implausibility mediate letter recognition processes by carefully controlling stimuli in two separate conditions. This would enable researchers to understand which factor is driving the effect, and further, whether differences in predictability relative to plausibility are simply reduced or qualitatively different. Differences could have important theoretical implications for sentence reading models that incorporate

[8] Thank you to an anonymous reviewer, who made this suggestion when this work was under review at *Cognition*.

multiple stages of word recognition, in which later stages are skipped if an upcoming word meets sentence expectations, such as the E-Z Reader (Reichle et al., 2003) and SWIFT model (Engbert et al., 2002; Engbert et al., 2005).

Future work would also benefit from developing a greater understanding of the division between biological and environmental constraints. Boundaries between biological and environmental influences on visual word recognition are blurred, as there is substantial evidence to show that visual and neural processes and structures adapt based on reading experience (Dehaene & Cohen, 2007; Grainger et al., 2010; Yablonski et al., 2019). Further, past work has shown that cross-linguistic differences can be dependent on task demands (Kinoshita et al., 2012; Lee et al., 2021). This latter finding highlights the risk of applying an overly dichotomous approach when classifying whether specific aspects of word recognition are due to universal cognitive processing or shaped by the written environment. Norris and Kinoshita (2012) suggest that the same basic perceptual processes are applied to processing orthographic information in all languages, and that readers then use this information differently to achieve optimal word discrimination under the demands of a specific writing system. Between-task differences provide insight of the depth and nature of processing required, for example, whether readers can attend to the task using low-level perceptual processing (e.g. same-different), broad lexical knowledge (e.g. lexical decision) or by identifying a specific word (e.g. reading aloud). Further work in this area would help to understand which processes are specialised to reading, and the influence of the written environment at different levels of representation. In turn, this can help delineate between theories of word recognition based on the extent to which they rely on specialised orthographic processing compared to domain general abilities.

As an additional consideration, understanding of the current findings could be enriched by investigating individual differences between readers. Despite extensive focus on the role of the written environment, the current work has little to say about the role of the reader as a navigator. Our results are based on group-level differences within demographically similar samples, which implicitly assumes the flawed notion that there is a prototypical reader (Yap et al., 2012). This is not ecologically valid, as reading processes are rarely uniform across readers. Skilled adult readers show wide variation in aptitude for the skills that underpin visual word recognition, such as spelling, vocabulary and grapheme-phoneme awareness (Yap et al., 2012). Variation in reading-related skills has been shown to mediate orthographic knowledge, and the extent to which processes are optimised based on the written environment. For example, readers with low grapheme-phoneme correspondence awareness demonstrate greater reliance on context to disambiguate between words with similar letters or pronunciations (Hersch & Andrews, 2012).

Examination of individual differences could provide further insights into the role of the reader during hierarchical integration of orthographic information. Readers with lower comprehension abilities may form weaker expectations for upcoming words within a sentence, which may increase their reliance on precise low-level visual information despite predictability from context. Individual reader differences may also have important consequences for the underlying neural representations of words, as probed in Chapter 6. There is evidence that morphological decomposition is mediated by individual differences in spelling and vocabulary (Andrews & Lo, 2013), and individual differences in morphological awareness have been shown to correlate with structural properties of white matter pathways in the brain (Yablonski et al., 2019). Therefore, individual differences may modulate the robustness of neural representations associated with morphemes. This could be addressed by conducting a battery of individual differences measures in order to isolate specific reading skills that are correlated with task performance (see Andrews, 2015). By investigating individual differences in the integration of bottom-up and top-down information, we can better understand how readers use existing cognitive abilities to interact with the written environment (Hersch & Andrews, 2012). This can help us to greater establish the role of the reader in theories of lexical representation and processing. Further, more could be learned about the role of the reader by collecting data from samples with greater diversity in reading skill. This may be more readily achieved by conducting data collection online to reach a more varied network of participants.

Finally, future research should continue to investigate the relationship between short-term contextual factors and long-term knowledge. This thesis has focused on these two aspects of visual word recognition independently, despite the fact that they are inextricably linked. For example, there is remaining ambiguity around the long-standing impact of contextual effects. Our findings demonstrated that surrounding sentence context has a profound effect on individual instances of visual word recognition, as recognition performance fluctuated dramatically across sentence frames, despite word targets remaining the same. Based on the variation within these results, contextual effects may be presumed to be fleeting and temporary. However, reading development research indicates that contextual information also has a long-term impact on how words are processed (Hsiao & Nation, 2018). Similarly, research comparing methods of reading instruction have demonstrated differences in behaviour and neural activity based on the manner in which words are taught (Taylor et al., 2017; Rastle et al., 2021). Both of these findings highlight the contribution of context in forming long-term representations of words.

In order to understand how word representations are formed, we must not only understand what the salient properties of the written environment are, but also the encompassing conditions under which they are learned. Future work could bridge the current gap by investigating how contextual information associated with individual instances of word recognition accumulates, and how this is integrated into long-standing word representations. New insights in this area would be particularly informative for theoretical accounts that incorporate statistical learning (e.g. Harm & Seidenberg, 2004; Plaut et al., 1996), as statistics used to inform these theories tend to be based on properties of words in isolation. By integrating the long-term role of context, this line of work could help develop a more sophisticated statistical account of learning that encapsulates both properties of the writing system and contextual task-based differences.

7.5 Conclusions

The aim of this thesis was to investigate how readers hierarchically integrate orthographic information during the initial stages of visual word recognition. Our findings indicate that the processes that underpin visual word recognition are signal-contingent based on the surrounding print environment. The evidence presented aligns with three key conclusions. Firstly, readers determine the precision of lower-level processing required based on cues from higher-level knowledge. Secondly, sub-lexical processing is not encapsulated within individual words. Instead, the influence of surrounding context transcends word boundaries to other words within a sentence. Finally, the weightings assigned to various sources of orthographic information vary cross-linguistically, as they are shaped by salient characteristics of the written environment. Overall, this research demonstrates that word recognition is achieved in a variable adaptive manner, as readers dynamically weight different sources of orthographic information based on immediate short-term context and long-standing knowledge of the writing system.

CHAPTER 7: DISCUSSION

This thesis more broadly highlights the consequences of studying specific reading processes in isolation, and how the overall picture might change when we consider how these processes vary across different contexts or writing systems. Whilst investigating how orthographic information is integrated during visual recognition, we exposed the fragility of well-established behavioural phenomena, such as the word superiority and transposed letter effects, and challenged the nature of why these effects occur. Future research would benefit from an integrated approach that considers both how reading processes emerge from the text environment, and how they interact with dynamic changes in surrounding orthographic context.

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