1. Introduction

1.1. Models of reading and functional units in reading

There is a rich history of research using computational models in reading, and they have demonstrated profound insights into reading and reading disorders, illuminating the cognitive processes required to map written letters onto spoken words. Such models have been used to decide between competing theoretical accounts that differ in terms of the mechanisms implicated in mapping between representations, but also in terms of precisely what the relevant representations
actually are within the reading system. The study reported in this paper combines computational modelling with a novel experimental paradigm to address each of these issues.

There are two proposed methods by which words may be identified. Either the word is identified holistically, as a single object, or it is identified by parts, whereby grain sizes smaller than the word are processed during word recognition. Such a debate has implications in both developmental and pedagogical domains, in terms of identifying potential sources of reading difficulties and monitoring reading acquisition, but also in terms of determining the appropriate grain size – letters, sets of letters, whole words – for training children to read most effectively.

There have been numerous computational models of reading created to improve understanding of the cognitive processes underlying our ability to map written words on to their spoken form. Models have differed in terms of whether they propose a single route forming the mapping [1-3] or whether there are two distinct routes [4-6], one involving sublexical mappings between letters and sets of letters and phonemes, the other mapping at the lexical level between written and spoken forms. Another issue at debate distinguishing different models of reading is whether in the architecture of the models the reading system operates serially left to right across the word or whether all letters in the word are simultaneously available. Different models have raised contrasting predictions regarding the functional units of the reading system with consensus remaining elusive.

There are a number of characteristics shared by dual-route models. The central unifying architectural feature is a lexical and sub-lexical route distinction. However in addition many also implement serial processing and explicit letter-grapheme relationships at either an input level or within the sub-lexical route. These two features are the prominent properties of the dual-route cascading model [4] and of more recent innovations that have adapted this modelling base incrementally [6]. In contrast, within single route models the reading system encodes the statistical relations, potentially at all levels of granularity, between patterns of letters and their pronunciation. Such models also tend to implement parallel processing of the visual input such that all letters in the words are simultaneously available [1-3]. The single-route architecture suggests that the functional units for reading will vary according to the useful statistical relations between letters and sounds, but that the word-level will not have a special architectural status independent from the sublexical mappings available within the vocabulary.
1.2. Theories of grain-sizes in reading

The link between variation in the functional units of reading and the statistical relations in letter sound mapping that emerges from single route models resonates with the Psycholinguistic Grain Size Theory of Ziegler and Goswami [7]. The theory describes the process of learning to read as acquiring the ability to find shared grain size in orthography and phonology. Grain sizes are therefore language specific, based on finding an efficient mapping between the two levels of representation. Ziegler and Goswami’s theoretical model proposes that the extent to which letters map regularly and compositionally onto phonemes in words, determines the type of processing that occurs in the reading system.

In languages with shallow orthographies such as Spanish or Italian where letter to phoneme mappings are largely one to one, the grain size that emerges is small. However for languages where correct pronunciation of an individual letter is dependent upon its context, the grain size that develops is related to the context required for correct pronunciation. English has been termed “pseudo-regular” [2] in that it has examples of both componential and one-to-one mappings, and such variation should thus be reflected in varying grain size for different words.

The grapheme has received particular attention in recent years as a reflection of a potentially effective grain size in reading, and has been explicitly implemented as such in the sublexical route of dual route models [6] of reading. Graphemes are defined as written representation of phonemes, and in English they can thus be composed of single or multiple letters (such as the digraphs CH, SH, or TH; or the trigraphs, SSI in mission, or TCH, in watch). What evidence is there for the special status of graphemes in reading, and how does this relate to decisions about the architecture of the reading system?

1.3. Rastle and Coltheart’s (1998) analysis of grain size

Rastle and Coltheart [8] tested the influence of graphemes on reading in the dual route cascading (DRC) model. In this model, the sublexical route processes letter by letter serially from left to right. Words are read by a combination of both the sublexical route and a lexical route, with explicit representations for each word. But nonwords are read exclusively by the sublexical route. If the DRC model is correct about the operation of the sublexical route, then nonwords containing pairs of letters that correspond to a single phoneme (i.e., digraphs), would result in a slowing of naming times. This was because in the model there is inhibition between phonemes generated by competing candidate graphemes. For the nonword fooce, for instance, the digraph “oo” competes with the single-
letter grapheme “o” in terms of pronunciation, and also the digraph “ce”, competes with the grapheme “c”. The consequence is that in the model nonwords containing five letters but three graphemes (e.g., fooce) were read more slowly than nonwords containing five letters and five graphemes (e.g., fruls). A behavioural study confirmed this prediction. Participants read the three grapheme nonwords more slowly than five grapheme nonwords. They concluded that the DRC model’s dual route mechanisms were confirmed – that for nonword reading, sublexical processing proceeds sequentially, with graphemes of different granularity competing in terms of pronunciation, indicating that the processing unit for reading is the letter – hence the competition between candidate combinations of letters, rather than naming time being positively correlated with the number of graphemes, this is dependent on the grapheme being the input level of representation for the sublexical reading system.

1.4. Alternative perspectives on the grapheme grain size for reading

The findings of Rastle and Coltheart [8] seem to be contradicted by a study investigating the granularity of representations used in reading in English [9]. In this alternative study, the performance of a computational model and behavioural studies testing reading under conditions of visual noise [9] seemed to indicate that the grapheme had a processing priority in reading for words. Pagliuca, Monaghan, and McIntosh [9] tested a single route model based on Harm and Seidenberg’s [6] connectionist model of reading. The model was trained to map between written and spoken forms of words for monosyllabic words in English. No explicit instruction was provided to the model in terms of how to solve this mapping, rather the model learned to exploit the useful regularities between certain patterns of letters and phonemes, which included letters, multi-word graphemes, and combinations of letters greater than graphemes, up to the whole word level. After training, the model was tested on two sets of five letter monosyllabic words, one containing digraphs in the initial word position, the other set containing no digraphs. When there was no impairment to the model’s input, then no difference in reading the digraphs and non-digraphs was found. However, when the input of the model was impaired by reducing the activation across the word along a monotonic gradient from left to right, simulating noise added to the visual presentation of the word, then words beginning with digraphs were read more accurately by the model than control words.
The same sets of words were employed in a behavioural study in which visual noise was applied in a continuous gradient across the word such that the leftmost letters were most impaired – see Figure 3 for an example stimulus. Pagliuca et al. [9] found that words containing digraphs were read more accurately than control words with no digraphs, confirming the predictions made by the model that digraphs were more robustly represented in the reading system than single letter graphemes.

Analysis of the model demonstrated that the advantage of digraphs for reading words was due to two input letter positions contributing to the activation of a single phoneme at the output, whereas for non-digraphs each letter only contributed to one phoneme’s activation. Consequently, when noise was applied to the visual input, words containing digraphs were read more accurately because greater activity percolated through the model from these two positions.

The study by Pagliuca et al. [9] provided evidence consistent with the hypothesis that graphemes are indeed functional units within the reading system, indicating that the grain size for reading in English is adaptable according to the statistics of the letter-sound mapping. When multi-letter graphemes are available then these are encoded within the reading system, but when single-letter graphemes are present then the single letter is the granularity applied by the reading system. Furthermore, this adaptive granularity in the model’s reading performance was due to encoding the useful levels of grain size in the mapping, rather than graphemes being explicitly encoded within the model.

1.5. Resolving conflicting views on granularity

The studies of Rastle and Coltheart [8] and Pagliuca et al. [9] therefore seem to present conflicting data on the representations used in the reading system, with consequences for different cognitive architectures for simulating human behaviour. However, there were a number of differences in the design of these studies that may have contributed to the difference in performance. First, the Rastle and Coltheart [8] study used nonwords, whereas the Pagliuca et al. [9] study tested word naming performance. Second, the Rastle and Coltheart [8] study tested presentations under normal conditions, whereas Pagliuca et al. [9] presented words under noise. We tested whether the model of Pagliuca et al. [9] would predict the same effects for nonwords as for words, and we also tested responses to both words and nonwords under noisy conditions in a behavioural study. If the nonword performance differed to words in the single-route model then this suggests that different mechanisms apply within the model for nonword reading, compared to word reading, with potentially different
contributions of grain size variations. If the nonwords were similar to the words in the model, then this suggests that the critical difference is the additional stress on the reading system of adding noise to the visual input. This would then indicate that the effects of graphemes on reading are subtle and only observable for words when the reading system is placed under stress. A further aim of our study was to extend the naming study of Pagliuca et al. [9] to another aspect of lexical processing – a lexical decision task. This enables us to validate the task across different dependent variables associated with lexical access.

2. Modelling word processing under noise

2.1. Method

2.1.1. Architecture

The model used was based upon Harm and Seidenberg’s [6] connectionist model of reading, and was the same as that used by Pagliuca et al. [9]. There were four layers of units in the model: an input orthographic layer, a hidden layer, an output phoneme layer, and an additional set of units producing phoneme attractor states.

![Figure 1. Architecture of the model](image)

The orthographic layer contained 10 letter slots, each represented by 26 units, with each of the 26 units corresponding to a single letter. A letter was represented by activating the unit assigned to the letter in the given slot, with all other units in that slot having zero activation. Words were represented by contiguous letter slots in the input being activated. The first vowel of the word
was placed in the fifth letter slot, with consonants preceding the vowel occupying letter slots to the immediate left of the vowel, and additional vowels and consonants following the first vowel occupying slots to the right of the first vowel.

The orthographic layer was fully connected to the hidden layer containing 100 units. These in turn were fully connected to the phonological output layer. This contained 8 phoneme slots with each phoneme represented in terms of 25 phonological features giving a total of 200 phonological units. There were two slots for the vowel, and three slots each for the onset and coda. The phonological units were self-connected (allowing basic dependencies between phonological features to be captured [6]) and connected to a set of 25 attractor units.

2.1.2. Training and testing

The model was trained on a corpus of 6229 monosyllabic words of length 1-10 letters extracted from the CELEX database. Frequencies were log compressed in the range [0.05,1], with values assigned to low frequency words capped at 0.05. The model was trained with a back-propagation learning algorithm [10] with a learning rate of 0.05. Initial connection weights were randomly assigned with mean 0, and variance 1. Training was capped at 5 millions cycles with words sampled randomly according to their frequency.

The stimuli used in testing consisted of four sets each containing 64 items. We selected words with digraphs in the onset, and control words with no digraphs, and also nonwords with digraphs in the onset, and a set of control nonwords with no digraphs. All stimuli were 5 letters in length and monosyllabic. The digraphs and the onsets of the control stimuli were the same as those used in Pagliuca et al. [9], the control words paired with SH digraph words began with the letters ST, control words paired with CH began with CR and control words paired with TH digraph words began with the letters TR. For the words, digraph and non-digraph stimuli were matched for same initial letter, unigram and bigram frequency, neighbourhood size, lexical frequency, body friends and body enemies (body friends are words with the same vowel and letters following the vowel with the same pronunciation of the vowel, whereas body enemies have similar spelling but different pronunciation), and partial view predictability (a measure of the likelihood of guessing a word given only part of the word was visible, when visibility is reduced from left to right across the word).

The nonwords were formed by switching onsets and rhymes within each word set, with changes in orthography mirrored in corresponding phonological
target representations. The nonwords were controlled for the same variables as the words, except for lexical frequency. Due to the digraph TH mapping on to two possible phonetic representations ‘D’ and ‘T’, TH items within the digraph nonword stimuli set were recorded as correctly reproduced if either phonological representation was outputted by the model.

Each stimulus set was presented to the model under three conditions of noise: (1) Perfect input (no noise) in which the input orthographic representation was activated as it was during training; (2) Gradient noise, in which there was monotonically increasing activation from left to right, as used in Pagliuca et al. [9], such that the activation was most reduced in the left most occupied letter slot and at full activation in the rightmost occupied letter slot. The reduction in activation was set at 25% of initial noise in the leftmost letter slot; and finally (3) Uniform noise, where activation was uniformly reduced across all letter slots by 50% of the level used during training. This additional noise condition was included to test the generality of the visual noise impairment, or whether the digraph effect only emerged if the digraph letters were most affected.

2.2. Results and Discussion

Two values were recorded to monitor model performance. Accuracy of the model’s performance was determined by taking the actual activation of the model’s production for each phoneme slot in the output, and determining whether that activation pattern was closer to the target phoneme than to any other phoneme in the language. The model was judged to have named the stimulus correctly, if each phoneme slot was accurately reproduced. An additional, more sensitive measure was taken to be the Euclidean distance of the output from the intended target for each phoneme slot. We report both measures, but the t-test calculations were performed only on the Euclidean distance unless otherwise stated. There are many ways in which models’ outputs are consulted to simulate behavioural responses to naming and lexical decision tasks (see [9] for a review). Our intention in the dependent variable for the model was to provide a reflection of the accuracy with which the model represented the stimulus, and given the high correlation between lexical decision and naming accuracies and response times, we propose that this is a reasonable approximation to behavioural studies designed to elicit variance in ease of lexical access.

After training, the model performed with an accuracy of 99.9% on the training set of words. For the digraph and control word sets, accuracy was 100% - see Figure 2.
When uniform noise was applied across the inputs, digraph words were read with lower error, $t(126) = 2.453, p < 0.01$. This was also the case when decreasing noise was applied across the input, $t(126) = 4.396, p < 0.01$. This replicated and extended the findings of Pagliuca et al. [9], showing that digraph words were less prone to effects of noise than were non-digraph words. When error only across the word onsets was calculated, significant differences were again found between performance on the digraph and control word sets, in both the uniform $t(126) = 4.876, p < 0.01$, and decreasing $t(126) = 10.668, p < 0.01$, noise conditions.

The model’s performance on nonword stimuli showed similar effects, see Figure 2. In the no noise condition, accuracy was high for both the digraph (84.4%) and control (92.2%) nonword sets, and at a level consonant with other models of nonword reading [1-5]. For uniform noise, just as for the words, digraph nonwords were read more accurately than control nonwords, $t(126) = 3.355, p < 0.01$, and this also pertained for the decreasing noise condition, $t(126) = 2.495, p < 0.01$. 

![Figure 2. Accuracy achieved by model in processing digraph and control words in perfect input, uniform noise and decreasing noise conditions.](image-url)
The results show the model to be sensitive to the presence of digraphs in both words and nonwords under conditions of noise. The model predicts that reading of digraph words and nonwords should both show an advantage under noisy conditions. We tested this prediction in a behavioural study.

3. Testing word and nonword reading under noisy conditions

3.1. Method

3.1.1. Participants

15 university students aged 18-29, participated in the study. All were native English speakers and had normal or corrected-to-normal vision.

3.1.2. Materials

The same word and nonword sets as were applied to the model were used in the study. Stimuli were presented in dark grey text (Courier New 150) on a greyscale background (300 x 100 px). Random 2-dimensional digital pixel noise was applied across the word in a decreasing gradient from left to right, so that the initial letter was most impaired (an example is shown in Figure 3).
3.1.3. Procedure

Participants were instructed to perform a lexical decision on each stimulus by pressing appropriate response keys on a keyboard. A fixation cross on a 300 x 100px greyscale background with decreasing gradient noise was presented for 1000ms. Then the stimulus was presented for 250ms and followed by a mask of decreasing gradient noise for 500ms. The next fixation cross appeared after a further 2000ms. Stimuli were presented in randomised order.

3.2. Results and Discussion

Figure 5. Mean accuracy of response in lexical decision task for words and nonwords with and without digraphs in onset (error bars represent standard error).
In line with the model’s prediction, words containing digraphs were responded to more accurately than control words, \( t(14) = 3.254, p<0.01 \). However, contrary to the model’s prediction, nonwords containing digraphs were responded to less accurately than controls, \( t(14) = 2.457, p<0.05 \), see Figure 5.

![Figure 6. Mean reaction time in lexical decision task for words and nonwords with and without digraphs in onset (error bars represent standard error).](image)

Reaction time data shows a similar trend although significance was not reached. Nonwords containing digraphs were responded to slower than nonwords without digraphs, with the reverse pattern shown in response to word stimuli.

4. General Discussion

The studies presented here explored the granularity of the reading system in English. In particular we investigated whether this grain size was adaptable as a consequence of the statistical properties of the language, namely whether the stimulus contained a digraph or not. We examined reading of words and nonwords with and without digraphs. Consistent with the findings of Pagliuca et al. [9] the model predicted better performance on digraph words under conditions of visual noise. The model also predicted similar patterns of effects for nonwords.

In our behavioural study, we confirmed that words containing digraphs were identified with greater accuracy than controls when visual noise was applied in a decreasing gradient across the word. These lexical decision results
confirmed the naming accuracy responses of Pagliuca et al. [9], and are consistent with the model’s predictions. However, for lexical decision on nonwords, nonwords containing digraphs were identified with less accuracy than control nonwords under visual noise conditions, in contrast with the predictions of the model.

Such an effect is consistent with the results of Rastle and Coltheart [8], who found that digraph nonwords were named more slowly than non-digraph nonwords, thus the effect of digraphs may be different for words than for nonwords. The results are partially consistent with the dual-route view of the reading system – that digraphs interfere with production of phonology for nonwords. However, the effect of digraphs on word naming and lexical decision is inconsistent with this view. Also, there are potentially dissociations between the effect of digraphs for nonword naming compared to lexical decision in the predictions of the DRC model. The DRC model implements lexical decisions in terms of activation of the orthographic lexicon, thus orthography-phonology mappings are largely irrelevant for lexical decisions [4], so it remains an open question as to how and whether digraphs may influence lexical decision for nonwords.

We favour the view that the effects of digraphs for word reading are subtle and only observable under conditions of noise – when the reading system is placed under stress. Hence, digraph effects should be the same for words as for nonwords within a single reading system. Finding critical data to distinguish between DRC and single-route models of reading has proved challenging, but we have here discovered a task where different predictions are made by each model. Under conditions of noise, we anticipate that nonword naming will support only one of these architectures.

The inverse effect of digraphs for nonwords compared to words may then be due to the simultaneous presentation of word and nonword stimuli in a single study, using lexical decision. Digraph nonwords were treated as more “word-like” than control nonwords, resulting in reduced accuracy for the digraph nonwords. The intermixing of words and nonwords in a single study, and measurement of a rejection for the nonword stimuli may have resulted in an impure measure of digraphs on nonword reading. Investigating naming accuracy for nonwords only under conditions of visual noise is required to resolve this issue.

A digraph effect was present in both simulation and behavioural data for both words and nonwords. For the model, there was a strong prediction that digraphs are functional units for both word and nonword reading. In respect to the behavioural data, this prediction is borne out for words, but not yet for
nonwords due to the potential difficulties of presenting both words and nonwords in the same study. However the presence of such an effect for words at least suggests that digraphs are functional units in reading and further indicates that the grain size for reading in English is adaptable according to statistics of the letter sound mapping, which provides interesting challenges to views on the independence of letter recognition [11], and demonstrates that word perception is affected by interdependencies between letters, resulting from letter-sound mapping statistics across the whole language. We have not yet firmly established the locus of digraph effects within the reading system – whether they are within one route of a dual route reading system, or whether they are hallmark features of a single route reading system responding to all the statistics mapping between sets of letters and phonemes. We have established, however, that digraphs have a prominent role in understanding the grain size of reading in English and in defining an adequate model of the reading system.

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References

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